

OmniDiMM: Bridging 1D, 2D, and 3D with Any-to-Any Multimodal Modeling

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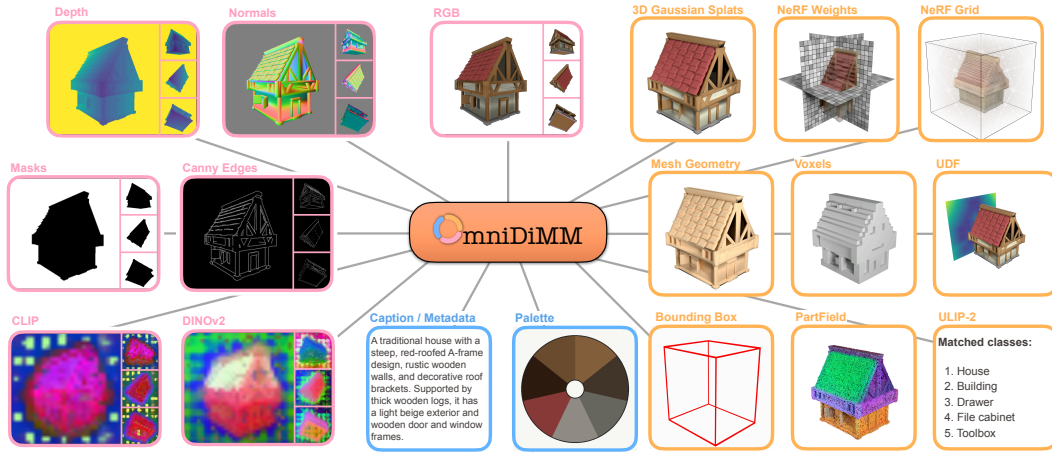


Figure 1: We introduce OmniDiMM, an any-to-any model that jointly processes a diverse set of 1D, 2D and 3D modalities. OmniDiMM can predict any modality conditioned on any one (or multiple) other modalities, enabling **out-of-the-box cross-modality prediction across dimensionalities**. The learned multimodal representations show strong performance on downstream tasks requiring both 2D and 3D understanding, including 3D pose prediction, grasp proposal, and object classification.

Abstract

The world appears spatially three-dimensional, however, existing large-scale multimodal models are often built mostly around 1D, 2D and 2.5D modalities. To move toward a more complete and actionable understanding of physical reality, models that natively model and generate across 1D, 2D, and 3D modalities are desirable. We present OmniDiMM, an any-to-any foundation model trained on diverse 3D including meshes, Gaussian splats, voxels, and NeRFs; 2D such as images, and 1D modalities like text. We develop tokenizers for diverse 3D modalities, such as NeRF weights triplanes, UDFs, and 3DGSs, that convert them into discrete tokens, which enables multimodal masked modeling for joint training. Out of the box, OmniDiMM can directly perform standard tasks such as novel-view image synthesis and 3D generation from images, where it matches or outperforms existing specialized methods. As an any-to-any model, it can also convert between different 3D representations, such as NeRF weights and UDFs, and generate various 3D modalities from 2D inputs, including DINOv2 features and surface normals. Joint training across 3D modalities also leads to strong transfer performance on down-

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stream tasks such as grasping, classification, and object pose prediction. We scale to 1T tokens across 1M objects and a 1B-parameter model. The pretrained models, training code, and multimodal dataset will be open-sourced.

1 Introduction

Biological perception is hypothesized to be constructed by integrating multiple sensory streams [123] such as visual, audio and haptic, each capturing partial aspects of the same underlying physical reality (Fig. 2). Leveraging connections among diverse modalities has been suggested to be critical for the development of biological intelligence [89]. In this spirit, recent multimodal foundation models have expanded beyond image-text learning to natively modeling diverse 1D and 2D(/2.5D) improving novel prediction and generation capabilities [72, 7, 65, 64]. However, we need not be limited to 1D and 2D modalities, as computational models can directly process 3D representations of the world, such as meshes [29], 3D Gaussian Splatting (3DGS) [52], and point clouds [78, 109] – if one can effectively bring diverse 3D modalities into the scaled pipelines.

Recent works attempt to leverage 3D representations typically by finetuning existing Vision-Language Models (VLMs) [22, 45] to ingest a single 3D format [38, 80, 44, 30], generate a 3D output [122, 86], or contrastively align a 3D modality with other 1D and 2D modalities [106, 90]. However, existing approaches have not yet scaled to model a diverse set of 3D modalities in the way they have for 1D and 2D data [72, 7, 65, 64]. To bridge this gap, we present OmniDiMM, an any-to-any *omni-dimensional multimodal model* trained jointly across 19 diverse 1D, 2D and 3D modalities (Fig. 1). These include 3D modalities such as meshes, Neural Radiance Fields (NeRFs) [71], 3DGS [52], voxels, Unsigned Distance Fields (UDFs), 3D part features [60] and global features [119], which are jointly trained with multi-view 2D modalities such as RGB, depth, CLIP feature maps, and text (1D).

OmniDiMM unifies the heterogeneous data space of each modality by mapping all inputs into a shared discrete token space (Fig. 3), allowing cross-modal learning with a joint multimodal masked modeling objective independent of the complexities of each modality. To accomplish this, we develop novel tokenizers for 7 diverse 3D modalities by transforming these modalities into a dense space which can be tokenized with VQ-VAE [98] based techniques (Sec. 3).

Any-to-any modeling allows controllable generation of arbitrary modalities using a single model. Similar to prior works with 1D and 2D modalities [72, 7], OmniDiMM can flexibly condition on, and generate, arbitrary combinations of modalities without the performance degradation typically associated with multitask learning, covering n modalities in a single model instead of $\mathcal{O}(n \times n)$ task-specific models. This single any-to-any architecture enables strong out-of-the-box performance on standard generative tasks, such as novel-view synthesis and 3D generation (Sec. 5.1), and unlocks novel feed-forward capabilities, such as direct translation between different 3D representations (e.g. predicting a NeRF from a 3DGS input, or a mesh from voxels). OmniDiMM also enables steerable generation from an arbitrary combination of conditioning modalities, for example, 3DGS from text and voxels (Sec. 5.2).

OmniDiMM also enables chained generation, where greater performance and structural consistency can be obtained on tasks by predicting intermediate modalities (RGB $\rightarrow$ DINO $\rightarrow$ Novel Views (RGB) $\rightarrow$ 3DGS) (Sec. 5.3). Finally, OmniDiMM learns a strong pre-trained representation for transfer to tasks that require 3D understanding of objects for effective performance, such as pose prediction or grasp proposal. Our core contributions are summarized as follows:

- **A Native 1D-2D-3D Multimodal Model.** Natively modeling 19 diverse modalities, OmniDiMM can resolve complex queries involving arbitrary input-output combinations, demonstrating strong out-of-the-box capabilities in 3D generation, novel-view synthesis, cross-3D translation, multimodal retrieval and steerable generations.

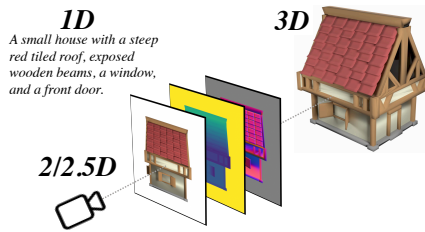


Figure 2: **Text, images, depth maps, and surface normals are views of a shared 3D physical reality.** Most existing foundational models have been trained on data representing these (comparatively lossy) 1D and 2/2.5D projections of reality. OmniDiMM can, in addition, operate directly on the 3D models that give rise to these projections.

- **Novel 3D Tokenization Strategies.** We develop discrete tokenizers for complex 3D representations, including NeRFs, Voxels, UDFs, and 3DGSs, enabling joint training.
- **3D-Aware Representations.** Joint multimodal training of OmniDiMM yields powerful representations, resulting in geometrically consistent generations and strong downstream performance on transfer tasks such as grasp and object pose prediction.

2 Related Works

Most recent works on foundation models unifying multiple modalities have primarily focused on images and text [81, 57, 59, 21]. Beyond this, several works incorporate additional modalities by unifying all input sources through tokenization [98, 23, 28], which abstracts modality-specific nuances [72, 7, 65, 64, 83, 102, 114, 115]. In particular, works such as 4M [72], 4M-21 [7] and UnifiedIO [65] have made large strides towards unification by jointly training a single model on a diverse set of up to 21 modalities. However, these efforts have largely omitted 3D data, which presents unique challenges. These include handling heterogeneous representation formats, the irregular or high-dimensional nature of its underlying structures, and the need to model complex spatial transformations.

Bringing 3D into this multimodal paradigm is an active area of research. A common strategy is to finetune existing VLMs to ingest a single 3D format [38, 80, 44, 30] or 2.5D signals [49, 48] alongside language, often for segmentation or grounding tasks and with the 3D components trained in relative isolation [22, 51, 133, 45]. Other approaches learn to predict a specific 3D output [122, 86], align 3D features with pretrained 1D and 2D embeddings via contrastive learning [118, 119, 128, 106, 90], or perform 3D generation conditioned on other modalities [126, 93, 95, 14], usually images or text. Although strong 2D Foundation models (FMs) exhibit some emergent 3D awareness [27] and can be adapted to 3D-related tasks [64, 1, 131], they still cannot natively ingest explicit 3D representations, limiting their ability to fuse 2D observations with explicit 3D geometric information. As a result, existing approaches remain restricted to specific tasks, a small set of modalities, or a single 3D representation. In contrast, OmniDiMM is pretrained jointly on a large-scale dataset spanning text, and diverse 2D and 3D modalities, enabling any-to-any prediction across 1D, 2D, and 3D modalities in a single model, unlocking new capabilities such as cross-3D translation and steerable 3D generation.

A related line of work is novel-view synthesis, which is typically addressed by specialized, camera-conditioned diffusion-based models [61, 54, 108]. However, these approaches are often restricted to a single fixed input type. In contrast, OmniDiMM can be finetuned for this task while being able to flexibly incorporate more conditioning signals such as additional RGB or depth images. This same flexibility also allows distilling powerful 3D representations developed by multi-view reconstruction methods [71, 52, 101, 55, 103] into OmniDiMM in the form of a modality that is included during pretraining.

3 Data, Modalities & Tokenization

Training a multimodal any-to-any FM is simplified by access to an aligned multimodal dataset, which enables the learning of inter-modality relationships [72]. To our knowledge, no such resource with diverse modalities exists for 3D data. We therefore construct one by augmenting publicly available 3D data. For OmniDiMM, we focus on object-level mesh data from Objaverse-XL [20], as it is the largest-scale publicly available form of textured 3D data. We use these textured meshes to create aligned modalities through geometric transformations (UDFs, voxels, etc.), neural representations (NeRF, etc.), rendering (RGB, depth, etc.), and pseudo-labeling (CLIP, DINOv2, etc.).

We train OmniDiMM on a diverse set of 3D, multi-view 2D and 1D modalities through joint masked modeling of all modalities. This requires compressing data from each modality into discrete *tokens*. However, techniques and models to tokenize most of the 3D modalities do not currently exist. Therefore, we create novel tokenizers for seven 3D modalities like NeRF weights, UDFs, and 3DGSs.

3.1 3D Modalities

We include eight 3D modalities in OmniDiMM: *Meshes*, *Voxels* and *UDFs* to aid understanding at varying levels of geometric detail; *3DGSs* [52] and *NeRF* [71] *weights* to enable high-quality textured 3D generation; *NeRF grids* [39] to represent explicit spatially organized texture information and finally *Part features* [60] and *ULIP-2 embeddings* [119], to embed an understanding of the local multi-

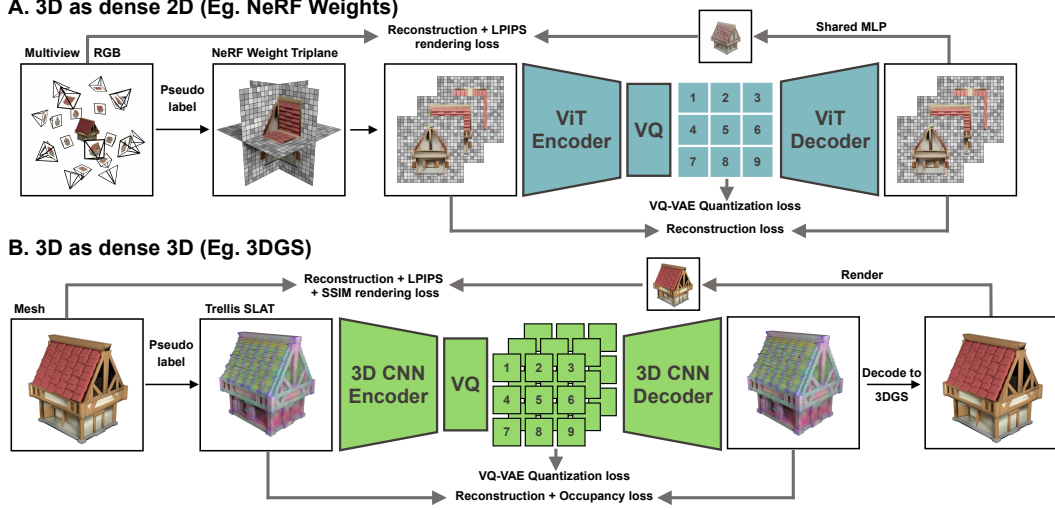


Figure 3: **3D Modality Tokenization:** We develop new tokenizers for 3D modalities with challenging to tokenize data formats. We cast these modalities into a space that is compatible with well-studied spatial VQ-VAE tokenizer architectures. **A)** We cast NeRF weights and part features as *triplanes*, which are split into multi-channel 2D data that are each tokenized with a 2D ViT tokenizer. **B)** We cast UDFs, voxels, 3DGSs and NeRF grids as dense 3D grids, which are tokenized with a 3D-CNN. Many modalities required tokenizer-specific training changes, such as rendering losses for NeRFs and 3DGSs and occupancy losses for Structured LATent (SLAT) latents; details are in Sec. B.

scale relationships of object parts and global semantics, respectively. We choose these modalities to both represent different variations of geometric, semantic, and texture information, and enable compatibility with various common 3D model types. Appendix A Sec. A provides a full description of these modalities.

To process these modalities, we require a tokenizer specific to each 3D modality. While tokenization of 1D [23, 96] and 2D modalities [1, 7] has been well-explored in prior works, models for the tokenization of 3D modalities are comparatively under-developed and either do not effectively scale to higher resolution data, are not abstracted enough to fit our modeling approach, or simply do not exist for a given modality. 3D modalities often have a more complex structure to account for, e.g., the consideration of empty space and non-uniform level of detail throughout a 3D model, such as the millions of Gaussians that comprise a 3DGS [52] or the sparse structure of SLATs [112]. Such data forms are challenging to tokenize with the well-studied techniques used for image-like and video-like data, complicating the process of learning tokenizers for these 3D modalities.

Instead of operating directly on these modalities, we curate our modality-generation methods to transform their complex structures into a form compatible with dense spatial VQ-VAE architectures [98] (Fig. 3), broadly described below. Additionally, we design modality-specific loss functions to enable high-quality reconstructions while maintaining a high level of abstraction. We include detailed descriptions and analyses of each of our tokenizers in Sec. B.

3D as dense 2D: *NeRF weights* and *Part features* are represented as *triplanes* [37] predicted by generalizable NeRF (Instant3D) [56] and part prediction (PartField) [60] models, respectively. These triplanes consist of 3 dense multi-channel 2D feature tensors which we tokenize using a modality-specific ViT-based [24] VQ-VAE tokenizer [98].

3D as dense 3D: *3DGSs* can be decoded from a sparse 3D SLAT which encodes high-fidelity 3D details. We densify SLATs from Trellis via zero padding to obtain a dense 3D grid representing *3DGSs*. *Voxels*, *UDFs* and *NeRF grids* are cast as dense 3D grids representing occupancy, distance to surface and RGB/density respectively and we train a 3D convolutional [97] VQ-VAE [98] on top of them.

Other 3D modalities: *ULIP-2 embeddings* are tokenized with a Bottleneck MLP [6] based on a discrete VAE with Memcodes [70]. Finally, for *Meshes* we use the pretrained Cube tokenizer [10], which performs well on our data.

3.2 1D and 2D Modalities

To enable OmniDiMM to learn the connection between 1D, 2D and 3D modalities, we include 8 multi-view tokenized 2D modalities and one textual modality. These are *RGB* images, *depth* and *surface normals* (providing 2.5D information), *canny edges* [12], *masks* (allowing to distinguish objects from their background), global DINOv2 [75] *features*, and *dense CLIP* [81] and *DINOv2* [75] *feature maps* (last three being useful to distill strong 2D features into OmniDiMM). We also take non-tokenized *Raw RGB* as an input, to facilitate transfer learning and simplify the application of augmentations for real-world adaptation. RGB, depth, normals and masks are obtained by rendering the object from multiple views with Blender [18]. From these renders, canny edges are extracted with OpenCV [11], and CLIP [81] and DINOv2 [75] features are extracted from pretrained models. Finally, we include *captions* for each object to align the learned representation with text, and enable the generation of both 3D and multi-view 2D modalities from language prompts. We use captions from Marvel-40M [127], and Cap3D [67, 68] which are externally pseudo-labelled from the meshes with GPT4-Vision [74].

We tokenize *RGB* and *depth* with COSMOS [1] and use the ViT-based [24] VQ-VAEs from 4M [7] to tokenize *surface normals*, *masks*, *canny edges*, and *dense feature maps*. Lastly, we tokenize *global DINOv2 embeddings* with a Bottleneck MLP [6], similarly to *ULIP-2 embeddings*, and *captions* using the Llama-2 tokenizer [96]. Fine-tuning is required to align the pre-trained tokenizers for surface normals and masks with our data; more details, along with the other 1D and 2D tokenizers, in Sec. B.

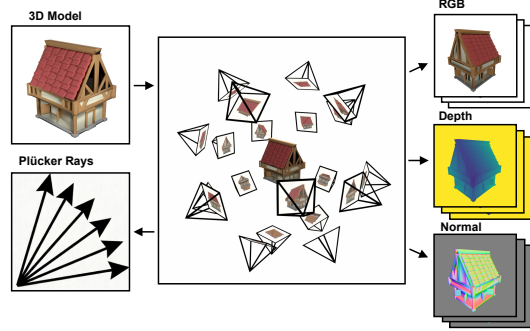


Figure 4: **Multiview 2D modalities** are rendered from the grounding mesh modality which are further tokenized per view with pretrained modality-specific tokenizers. Plücker rays are extracted from the camera coordinates for use as positional embeddings in training (see Fig. 5).

4 Modeling

To perform joint learning on a range of 1D, 2D and 3D modalities, we optimize OmniDiMM with the multimodal masked modeling objective introduced in 4M [72, 7]. Following prior work [7, 65], we represent each modality as a set of discrete tokens using modality-specific tokenizers. This enables any-to-any prediction among a diverse set of 1D, 2D and 3D modalities OmniDiMM accepts, thereby enabling a range of capabilities such as single or multi-view 2D to 3D generation, novel view synthesis between any modalities, generation from text, and any other combination of conditioning and target modalities (Fig. 7).

Dataset: We train OmniDiMM on a subset of Objaverse-XL [20], the largest publicly available 3D mesh dataset, consisting of 1 million objects. While this dataset has a small number of samples in comparison to the dataset used to train foundation models on 1D and 2D modalities, the wide range of modalities and heavy masking used allows us to train a billion parameter model with only this data. We provide more details about the dataset and modality creation procedure in Sec. A.

Model: We employ a Transformer-based encoder-decoder [99] architecture to learn joint prediction of tokens across modalities similar to 4M [72] (Fig. 5). The only modality-specific information provided to OmniDiMM is per-modality positional encoding of tokens. As the model requires to both distinguish between different views of the multi-view 2D modalities, and learn their relationship to the 3D modalities, we use a learned projection of the Plücker rays [77] corresponding to the camera used to generate a given token image patch [125]. We use 3D sine-cosine embeddings, a natural extension of the standard handling of dense image-like modalities [24], to encode the position of tokens for dense 3D modalities such as UDFs, and image-like 3D modalities relying on triplanes. Since mesh and ULIP-2 [119] tokens are not spatially organized, we use learned positional embeddings. For captions, we use standard 1D sine-cosine embeddings [99]. Each modality also learns a modality-specific embedding as a unique identifier of the data class to which a given token

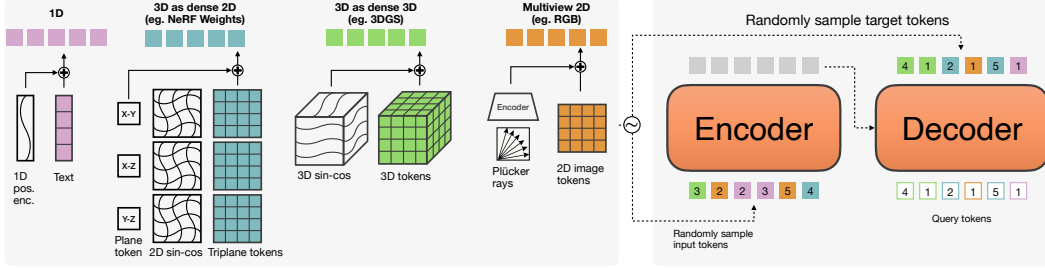


Figure 5: **The OmniDiMM Model:** **Left:** We augment the tokenized modalities with a positional embedding corresponding to their structure. We use 2D sin-cos embeddings for 3D modalities cast as dense 2D, 3D sin-cos embeddings for 3D modalities cast as dense 3D and encoded plucker rays are used for multiview 2D modalities. **Right:** OmniDiMM is a Transformer that we train on the masked modeling objective introduced in 4M [72]. A small subset of the tokens from all modalities are sampled as the context the transformer uses to predict a different random subset of tokens from all modalities.

belongs. Various other components of the standard Transformer architecture were modified to improve training performance and efficiency, detailed in Sec. C.

Data sampling: Several of the previous modalities require large token counts relative to previous multimodal masked modeling works [72, 7] due to either the presence of multi-view data or of complex modalities that require high token counts to compress while maintaining the required fidelity. When training, we strongly mask our data, maintaining approx. 2% of all tokens as inputs for the encoder and decoder. This combination of a diverse range of modalities and heavy masking would result in key joint learning tasks being observed infrequently by OmniDiMM under a naive random sampling scheme. To mitigate this issue, we employ a wide range of sampling mixes to cover key tasks such as RGB to 3D and novel view 2D synthesis. We provide a complete description of the sampling approaches in Sec. D.

Training: OmniDiMM is a 1B parameter model and was trained for 1T tokens, with 512 target tokens being predicted from 512 conditioning tokens for each step. We use a WSD scheduler [26] for the learning rate, with hyperparameters transferred from a small-scale proxy optimized with μ -P [120]. Please refer to Sec. E for the full training details.

5 Multimodal Generative Capabilities

OmniDiMM can generate all modalities from a given input modality (Fig. 6), where both inputs and outputs for 2D modalities can be single- or multi-view. This enables us to perform several standard tasks, such as novel-view synthesis and 3D generation, out of the box, while also performing other generations, such as voxel to NeRF that existing models are not capable of.

5.1 Novel View Synthesis and 3D Generation

OmniDiMM supports both novel-view synthesis and direct 3D asset generation from one or more input views, and can condition on arbitrary 2D modalities such as RGB images, feature maps, depth, and normals, either individually or in combination. In both settings, we find that performance benefits not only from the shared multi-modal pretraining of OmniDiMM, but also from richer conditioning at inference time. For fair comparison with prior work, we primarily evaluate in the single-image setting supported by all baselines, while also reporting multi-view results when supported.

For evaluation, we use the GSO [25] dataset and a held-out test split of Objaverse-XL [20]. We follow the same input-view sampling protocol across tasks, using six random conditioning and target camera poses that include both informative and challenging views, rather than restricting evaluation to only favorable viewpoints. As shown in Fig. 7 and Tab. 1, OmniDiMM matches or outperforms existing methods on most metrics for both novel-view synthesis and 3D generation. In the 3D generation setting, we additionally compare multi-view conditioning, where OmniDiMM achieves the strongest overall results.



Figure 6: OmniDiMM can generate all modalities from a single input with a high degree of cross-modal consistency. Modalities highlighted green are 3D, while modalities highlighted grey are multi view 2/2.5D. All 2/2.5D modalities can be generated from arbitrary viewpoints, an example of which is given for RGB in the orange highlighted column. The model has learned useful priors about the world (note that the leaves on the tree are almost always green, even when generated from modalities with no texture information) which aids in generation from lower-information modalities such as masks and voxels.

The any-to-any design of OmniDiMM also enables inference-time chaining through intermediate modalities. For novel-view synthesis, we improve results by first predicting DINOv2 [75] feature maps and surface normals before generating the target RGB view. For 3D generation, we similarly find that first predicting additional RGB views and then using them as extra conditioning improves the quality of the generated 3D assets. We explore this in detail in the following Sec. 5.3.

5.2 Any-to-Any Generation and Retrieval Capabilities

As OmniDiMM was trained with an any-to-any token prediction modality, it is capable of predicting *any* 1D, 2D or 3D modality from *any* other modality, without constraints. This enables our model to natively perform many tasks out of the box (fig. 8) that would otherwise either require specialized handling, such as rendering and texturing, or would be too costly for specialized models to be trained for, such as novel view synthesis in depth or edge image space. As we use text captions as a modality, OmniDiMM can also steer generation of high quality textured samples from low resolution conditioning modalities in 2D and 3D.

OmniDiMM can also perform retrieval by predicting global DINOv2 or ULIP embeddings for a given input and matching against a pre-existing or similarly generated retrieval set by minimizing cosine distance. Importantly, this retrieval can be performed between *any* modality of *any* dimensionality.

Novel View Synthesis								
Dataset	Method	PSNR $\uparrow$	LPIPS $\downarrow$	SSIM $\uparrow$	MS-SSIM $\uparrow$	FD _{incep} $\downarrow$	FD _{DINOv2} $\downarrow$	KD _{DINOv2} $\downarrow$
GSO [25]	Ouroboros [108]	13.660	0.271	0.757	0.666	51.398	547.244	110.432
	Zero123 [61]	15.262	0.239	0.793	0.742	17.046	8.633	0.744
	OmniDiMM (Ours)	20.966	<u>0.193</u>	0.769	0.828	30.327	8.633	0.277
	OmniDiMM (Ours) (C)	<u>20.669</u>	0.191	<u>0.770</u>	<u>0.820</u>	<u>24.675</u>	<u>17.218</u>	0.999
Objaverse-XL [20]	Ouroboros [108]	14.332	0.254	0.797	0.695	40.319	31.339	3.876
	Zero123 [61]	14.721	0.238	0.816	0.746	13.667	<u>3.601</u>	<u>0.361</u>
	OmniDiMM (Ours)	16.983	<u>0.186</u>	0.788	<u>0.846</u>	18.890	<u>3.601</u>	<u>0.361</u>
	OmniDiMM (Ours) (C)	20.013	0.178	<u>0.800</u>	0.851	<u>15.850</u>	2.814	0.205
3D Generation								
Dataset	Method	PSNR $\uparrow$	LPIPS $\downarrow$	SSIM $\uparrow$	MS-SSIM $\uparrow$	FD _{incep} $\downarrow$	FD _{DINOv2} $\downarrow$	KD _{DINOv2} $\downarrow$
GSO [25]	Trellis [112]	15.552	0.254	0.766	0.691	16.141	<u>67.613</u>	<u>6.435</u>
	SAM3D [13]	15.167	0.232	0.784	0.718	<u>19.320</u>	17.666	1.562
	OmniDiMM (Ours)	<u>16.286</u>	<u>0.230</u>	<u>0.787</u>	<u>0.730</u>	45.650	76.070	7.316
	OmniDiMM (Ours) (C)	17.048	0.207	0.801	0.755	43.526	74.937	6.878
	Trellis (MV) [112]	<u>16.382</u>	<u>0.224</u>	<u>0.782</u>	<u>0.722</u>	16.976	60.219	5.583
Objaverse-XL [20]	OmniDiMM (Ours) (MV)	17.054	0.203	0.803	0.759	<u>46.004</u>	<u>80.905</u>	<u>7.676</u>
	Trellis [112]	13.621	0.283	0.780	0.688	<u>14.033</u>	30.038	2.149
	SAM3D [13]	14.484	0.261	0.783	0.696	10.407	13.435	0.792
	OmniDiMM (Ours)	<u>14.607</u>	<u>0.252</u>	<u>0.787</u>	<u>0.712</u>	22.676	17.584	1.338
	OmniDiMM (Ours) (C)	15.044	0.234	0.796	0.729	20.458	<u>15.855</u>	<u>0.988</u>
	Trellis (MV) [112]	<u>14.087</u>	<u>0.262</u>	<u>0.790</u>	<u>0.708</u>	14.398	<u>29.894</u>	<u>2.058</u>
	OmniDiMM (Ours) (MV)	15.056	0.232	0.797	0.731	<u>20.906</u>	16.029	1.084

Table 1: **Novel view synthesis and 3D generation.** OmniDiMM generally matches or surpasses specialized prior methods for single-image novel view synthesis and 3D generation, and performs best overall for multi-view 3D generation (MV: 6 input images). **Chained generation.** Using intermediate predictions at inference time (C) further improves results: DINOv2 features and normals condition target-view RGB synthesis, while five predicted RGB views condition final 3DGS generation.

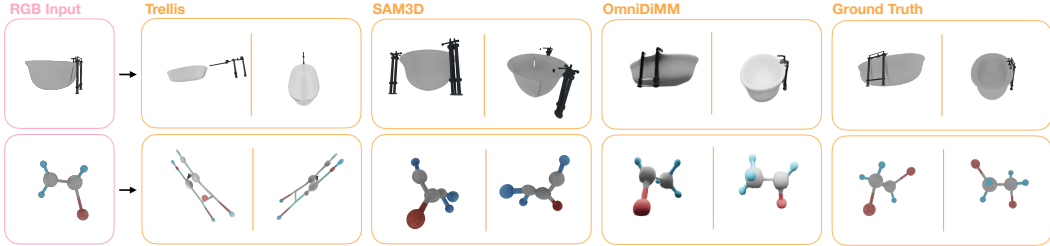


Figure 7: **Qualitative comparison of 3D generation.** Our model outperforms prior single-view 3D generation methods, especially under ambiguous, self-occluded inputs, while preserving geometric coherence across target views. We compare against Trellis [112] and SAM3D [13], which support arbitrary relative-pose generation. See the supplementary for additional qualitative results.

As shown in fig. 9 (in the Appendices) we find that both embeddings are useful for different retrieval targets; global DINOv2 embeddings are effective at retrieving similar views of 2D modalities with related semantic meaning, while ULIP is effective for matching full object geometric characteristics.

5.3 Chaining

The any-to-any design of OmniDiMM enables inference-time chaining through intermediate modalities. During inference, instead of directly generating a target ($\mathcal{T}$) from the provided input ($\mathcal{I}$), we generate intermediate outputs ($\mathcal{O}_i$) from the model and add them as additional conditioning to the model for generating the target. Specifically:

$$\text{Direct: } \mathcal{I} \rightarrow \mathcal{T} \quad \bigg| \quad \text{Chained: } \mathcal{I} \rightarrow \mathcal{O}_1 \text{ then } \mathcal{I} + \sum_{i=1}^j \mathcal{O}_i \rightarrow \mathcal{O}_{j+1} \text{ then } \mathcal{I} + \sum_{i=1}^N \mathcal{O}_i \rightarrow \mathcal{T} \quad (1)$$

The intermediate outputs ($\mathcal{O}_i$) can be a view of any multi-view 2D modality (RGB, DINOv2, etc.) or any other modality (voxels, text, etc.). For novel-view synthesis, we find that first predicting DINOv2 [75] feature maps and surface normals before generating the target RGB view produces better results as shown in Tab. 1. For 3D generation, we similarly find that first predicting additional

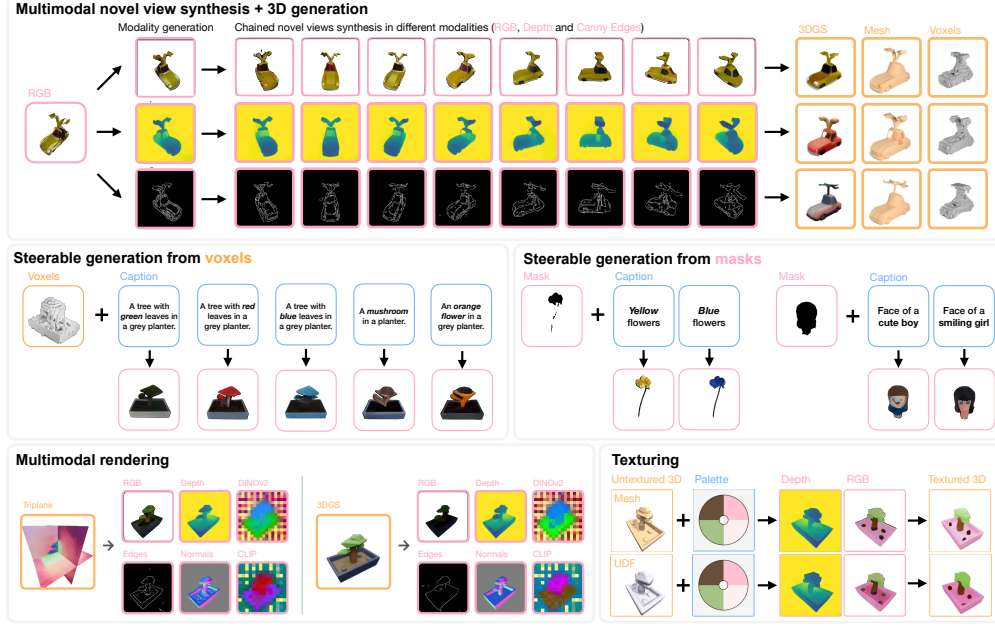


Figure 8: **Capabilities enabled by any-to-any modelling.** OmniDiMM is natively capable of completing a diverse array of tasks due to the any-to-any training approach. **Top:** NVS can be performed with any 2D modality, and any of these chains of novel views can be used to predict 3D modalities. **Middle:** Our model can up-sample low information 2D (masks) and 3D (voxels) inputs steered by text, enabled by the caption modality of our model. **Bottom left:** Our model can render any 2D modality from 3D models without requiring explicit rendering equations. **Bottom right:** Our model can texture 3D models by predicting textured modalities jointly conditioned on an untextured 3D modality and a texture to be applied.

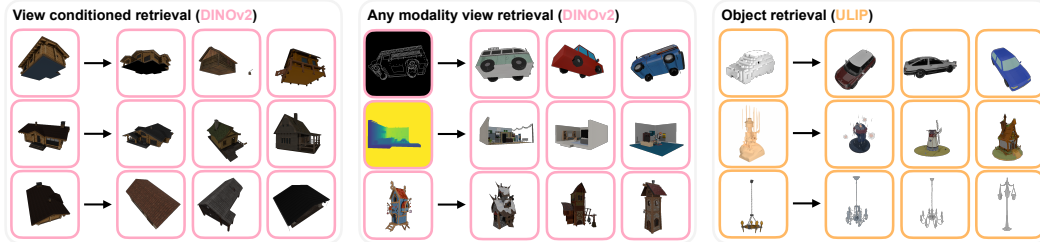


Figure 9: **Retrieval with OmniDiMM** across any modality of any dimensionality by predicting and matching global embeddings. **Left:** Global DINOv2 embeddings are strongly correlated with camera pose, enabling view-aligned retrieval. **Middle:** Retrieval can be done using any modality due to our model’s any-to-any prediction capabilities. The strong view correlation of Global DINOv2 embeddings still holds across modalities. **Right:** Retrieval with ULIP embeddings correlates with the geometric structure of objects and so can be used to perform view independent retrieval.

RGB views and then using them as extra conditioning improves the quality of the generated 3D assets (see Tab. 1 and Fig. 13).

Chaining also enables the generation of high-complexity modalities such as 3DGS from low-complexity modalities such as text and voxels. We find that chaining through intermediate 2D modalities provides guidance that enables our model to effectively answer these under-constrained tasks that it can struggle to perform through direct prediction.

5.4 Analysis

Joint 1D-2D-3D training: In order to identify the benefits of joint training across 1D, 2D and 3D modalities, we perform a compute matched ablation, of training only on 1D and 2D modalities. For comparison, we test the performance of both models on a 2D task, which is, novel-view synthesis.

Table 2: **Robustness to unposed and non-canonical inputs.** We progressively relax the canonical input assumptions of OmniDiMM using predicted pose, scale/shift normalization, and camera roll. The small gap between ground-truth and predicted-pose performance on both Objaverse-XL and the out-of-distribution GSO dataset demonstrates OmniDiMM’s robustness to in the wild images.

Dataset	Method	PSNR $\uparrow$	LPIPS $\downarrow$	SSIM $\uparrow$	MS-SSIM $\uparrow$	FD _{Incep} $\downarrow$	FD _{DINOv2} $\downarrow$	KD _{DINOv2} $\downarrow$
Objaverse-XL (2k)	GT pose	20.113	0.188	0.716	0.840	18.821	14.058	1.597
	Predicted pose (pose-flow)	19.652	0.197	0.705	0.826	19.010	14.401	1.646
	+ Normalized (pred scale/shift)	17.934	0.251	0.504	0.742	22.930	46.989	7.463
GSO [25]	GT pose	21.945	0.203	0.683	0.808	26.551	26.250	2.834
	Predicted pose	21.642	0.209	0.674	0.798	26.721	26.497	2.916
	+ Normalized (pred scale/shift)	20.201	0.244	0.517	0.744	30.625	48.290	8.535
	+ Arbitrary roll (pred un-roll)	18.509	0.298	0.487	0.680	34.702	46.778	8.038

As shown in Tab. 3), we find that joint training with all modalities outperforms training without 3D modalities, demonstrating the benefit of joint 1D-2D-3D multimodal training.

Method	PSNR $\uparrow$	LPIPS $\downarrow$	SSIM $\uparrow$	MS-SSIM $\uparrow$
2D Only (500B tok)	22.911	0.152	0.783	0.833
OmniDiMM (500B tok)	23.739	0.126	0.816	0.857
OmniDiMM (1T tok)	24.151	0.121	0.819	0.864

In-the-wild performance: OmniDiMM is trained on objects represented in a canonical Objaverse camera frame. To extend the model to unposed images, we therefore predict the transformation required to map an arbitrary input image into this canonical frame. Given a single RGB image, we first use a flow-matching pose estimator to predict the corresponding Objaverse-aligned camera pose while accounting for azimuthal ambiguities. We additionally predict the scale and image-plane shift required to match the object framing seen during training, and use a separate predictor to compensate for arbitrary camera roll.

Table 2 evaluates these components progressively. On held-out Objaverse-XL, replacing ground-truth poses with predicted poses results in only a small degradation (20.113 to 19.652 PSNR), showing that the downstream model is robust to realistic pose-prediction errors. More importantly, although the pose predictor is trained exclusively on Objaverse, the same behavior transfers to GSO: performance decreases only from 21.945 to 21.642 PSNR when replacing ground-truth with predicted poses. This suggests that the pose predictor generalizes beyond the distribution on which it was trained. Predicting scale/shift and handling arbitrary roll further relax the assumptions on the input, at the cost of progressively larger degradation as errors accumulate across the canonicalization pipeline.

Table 3: **Ablation on modalities.** OmniDiMM trained on all modalities outperforms a model trained without 3D modalities on NVS. (Training tokens)

6 Transfer Learning

We demonstrate the benefits of pretraining on a range of 2D and 3D modalities by transferring the pretrained encoder to three diverse downstream tasks. To adapt OmniDiMM, we finetune the pretrained encoder using Low-Rank Adaptation (LoRA) [40] and attach task-specific heads trained from scratch. We employ an optimizer with layer decay to ensure the effective learning rate is higher in the later layers. Further training details are provided in Sec. F.

2D Object Pose Estimation: To demonstrate the applicability of OmniDiMM to single-view 3D tasks, we adapt it to category-level pose estimation via Normalized Object Coordinate Space (NOCS) [100]. This task maps observed 2D pixels to a canonical 3D representation, explicitly testing the model’s ability to relate a 2D view to its underlying 3D geometry. We attach the prediction head from OmniNOCS [53] to our pretrained encoder, which predicts NOCS and segmentation masks from the raw RGB input. As shown in Sec. 6, OmniDiMM significantly outperforms the NOCS baseline [100]. Fig. 10 illustrates that using the OmniDiMM backbone, one can accurately infer both 3D canonical coordinates and instance masks from diverse 2D observations.

Method	NOCS MAE $\downarrow$	NOCS PSNR $\uparrow$	Mask IoU $\uparrow$
NOCS [100]	0.121	16.345	86.10
OmniNOCS (zero-shot) [53]	0.107	18.527	89.03
OmniDiMM (Ours)	0.018	27.315	94.4



Figure 10: **Object Pose (NOCS) Estimation.** Comparison of transfer performance on NOCS-Real275 (*top*) and qualitative examples of OmniDiMM’s performance (*bottom*).

Method	Suc.6 $\uparrow$	Suc.1 $\uparrow$	Pen. $\downarrow$	Div $\uparrow$
UniDexGrasp [117]	23.7	65.5	24.5	0.14
GraspTTA [50]	21.0	65.3	21.2	0.10
SceneDiffuser [46]	28.3	74.8	25.1	0.15
UGG [66]	46.0	83.2	24.5	0.14
DGA [130]	54.8	90.8	18.9	0.25
DGA w/ LLM [130]	53.1	91.2	18.8	0.23
OmnDiMM (Ours) w/ standard diffusion sampling	3.6	83.9	13.2	0.11
OmnDiMM (Ours) w/ physics-guided sampling [130]	83.3	96.7	15.9	0.16

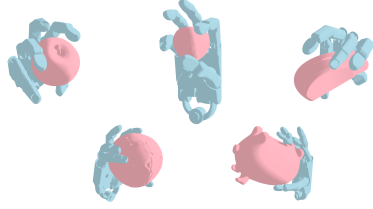


Figure 11: **Grasp prediction.** *Left:* OmnDiMM shows strong transfer performance on MultiDex [58], including grasp success rates (Suc.6 and Suc.1), maximum penetration, and diversity. A grasp is successful if perturbations displace the object by ≤ 2 cm in at least one axis-aligned direction (Suc.1) or in all six directions (Suc.6). *Right:* sample grasp predictions. We compute these metrics by simulating the predicted grasps in IsaacGym [69].

Grasp Prediction: We also evaluate OmnDiMM to predict physically plausible and stable grasps. We adapt the DexGrasp Anything model [130] and replace the Point Transformer [129] encoder while keeping the diffusion-based head that predicts ShadowHand parameters. We use raw RGB images as input and train the model end-to-end using the physics-aware losses of DexGrasp Anything [130]. As shown in Fig. 11, OmnDiMM can be used to predict successful grasps for objects with varied shapes, sizes, and from different approaching directions.

Object classification: We evaluate 3D object classification on ModelNet40 [111]. To adapt OmnDiMM for classification, we use a mixture of multimodal input tokens and pool the encoder’s output features using cross-attention with learned queries representing each of the 40 classes. In Tab. 4, we report the top-1 accuracy using two distinct modality combinations: 2D/3D semantic (ULIP-2 [119] 3D features, alongside DINOv2 [75] and CLIP [81] patch features from five random views) and 3D-only (ULIP-2 [119] features, UDFs, and voxel grids). OmnDiMM effectively synthesizes these inputs, achieving a competitive performance that closely matches fully supervised, task-specific architectures. Furthermore, by contextualizing the inputs through our any-to-any architecture, the model substantially improves over the zero-shot capabilities of the base ULIP-2 [119] features it ingests.

Further experimental results and implementation details for the transfer tasks are reported in the Appendix.

7 Limitations and Discussion

OmnDiMM is a large-scale any-to-any foundation model capable of processing and generating data across a diverse range of 19 modalities, spanning 1D, 2D, and 3D. To achieve such levels of multi-modality, we unify all input sources through tokenization [98, 23, 28], which abstracts modality-specific nuances [72, 7, 65, 64, 83, 102, 114, 115]. We build upon existing tokenizers [1, 72, 7, 96] for 1D and 2D modalities, and propose novel solutions to tokenize complex 3D representations such as NeRF weights, UDFs, and 3DGSSs. We demonstrate that the joint masked modeling pretraining used for OmnDiMM can effectively unify all the modalities and enable any-to-any generation tasks. Below, we discuss the limitations of our current model and future work to rectify these limitations.

Tokenization bounds: Due to the lack of pre-existing tokenization methods for many 3D modalities, we were required to develop our own tokenizers for this work. While these tokenizers perform well, more focused research on improving tokenization for each 3D modality would raise the ceiling of our model’s performance.

Data and model scale: While our any-to-any learning objective enabled training a strong model on only 1M samples, multimodal models in 1D and 2D domains are trained on orders of magnitude more data. As access to 3D data, as well as clever ways of using more scaled 2D data toward extracting 3D priors, progress, we expect to see further improvements in our model.

Table 4: **3D object classification transfer.** Results on ModelNet40 [111] show OmnDiMM can achieve competitive results and successfully incorporate information from diverse 2D and 3D input modalities.

Method	Accuracy $\uparrow$
DGCNN [105]	0.926
PointNet++ [79]	0.930
SimpleView [32]	0.939
GDANet [116]	0.934
CurveNet [113]	0.938
RPC [84]	0.930
ULIP-2 (zero-shot) [119]	0.847
OmnDiMM (Ours) 2D/3D semantic	0.932
OmnDiMM (Ours) 3D-only	0.927

Pose usage for 2D modalities: Our model requires the camera pose of 2D modalities as positional embeddings, which adds a complication to multi-view operation from sensors that do not have access to their pose. While this limitation can be mitigated using post estimation methods, fully removing the requirement for known poses at inference time would simplify its use.

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References

- [1] Niket Agarwal, Arslan Ali, Maciej Bala, Yogesh Balaji, Erik Barker, Tiffany Cai, Prithvijit Chattopadhyay, Yongxin Chen, Yin Cui, Yifan Ding, Daniel Dworakowski, Jiaojiao Fan, Michele Fenzi, Francesco Ferroni, Sanja Fidler, Dieter Fox, Songwei Ge, Yunhao Ge, Jinwei Gu, Siddharth Gururani, Ethan He, Jiahui Huang, Jacob Huffman, Pooya Jannaty, Jingyi Jin, Seung Wook Kim, Gergely Klár, Grace Lam, Shiyi Lan, Laura Leal-Taixe, Anqi Li, Zhaoshuo Li, Chen-Hsuan Lin, Tsung-Yi Lin, Huan Ling, Ming-Yu Liu, Xian Liu, Alice Luo, Qianli Ma, Hanzi Mao, Kaichun Mo, Arsalan Mousavian, Seungjun Nah, Sriharsha Niverty, David Page, Despoina Paschalidou, Zeeshan Patel, Lindsey Pavao, Morteza Ramezanali, Fitsum Reda, Xiaowei Ren, Vasanth Rao Naik Sabavat, Ed Schmerling, Stella Shi, Bartosz Stefaniak, Shitao Tang, Lyne Tchapmi, Przemek Tredak, Wei-Cheng Tseng, Jibin Varghese, Hao Wang, Haoxiang Wang, Heng Wang, Ting-Chun Wang, Fangyin Wei, Xinyue Wei, Jay Zhangjie Wu, Jiashu Xu, Wei Yang, Lin Yen-Chen, Xiaohui Zeng, Yu Zeng, Jing Zhang, Qinsheng Zhang, Yuxuan Zhang, Qingqing Zhao, and Artur Zolkowski. Cosmos world foundation model platform for physical ai. *arXiv:2501.03575*, 2025.
- [2] Adel Ahmadyan, Liangkai Zhang, Artsiom Ablavatski, Jianing Wei, and Matthias Grundmann. Objectron: A large scale dataset of object-centric videos in the wild with pose annotations. In *CVPR*, 2021.
- [3] Takuya Akiba, Shotaro Sano, Toshihiko Yanase, Takeru Ohta, and Masanori Koyama. Optuna: A next-generation hyperparameter optimization framework. In *SIGKDD International Conference on Knowledge Discovery and Data Mining*, 2019.
- [4] Ibrahim M Alabdulmohsin, Xiaohua Zhai, Alexander Kolesnikov, and Lucas Beyer. Getting vit in shape: Scaling laws for compute-optimal model design. *NeurIPS*, 36:16406–16425, 2023.
- [5] Jimmy Lei Ba, Jamie Ryan Kiros, and Geoffrey E Hinton. Layer normalization. *arXiv:1607.06450*, 2016.
- [6] Gregor Bachmann, Sotiris Anagnostidis, and Thomas Hofmann. Scaling mlps: A tale of inductive bias. *arXiv:2306.13575*, 2023.
- [7] Roman Bachmann, Oğuzhan Fatih Kar, David Mizrahi, Ali Garjani, Mingfei Gao, David Griffiths, Jiaming Hu, Afshin Dehghan, and Amir Zamir. 4M-21: An any-to-any vision model for tens of tasks and modalities. In *NeurIPS*, 2024.
- [8] Gilad Baruch, Zhuoyuan Chen, Afshin Dehghan, Tal Dimry, Yuri Feigin, Peter Fu, Thomas Gebauer, Brandon Joffe, Daniel Kurz, Arik Schwartz, and Elad Shulman. ARKitScenes - A Diverse Real-World Dataset for 3D Indoor Scene Understanding Using Mobile RGB-D Data. In *NeurIPS*, 2021.
- [9] Shane Bergsma, Nolan Dey, Gurpreet Gosal, Gavia Gray, Daria Soboleva, and Joel Hestness. Power lines: Scaling laws for weight decay and batch size in llm pre-training. *arXiv:2505.13738*, 2025.
- [10] Kiran Bhat, Nishchaie Khanna, Karun Channa, Tinghui Zhou, Yiheng Zhu, Xiaoxia Sun, Charles Shang, Anirudh Sudarshan, Maurice Chu, Daiqing Li, et al. Cube: A roblox view of 3d intelligence. *arXiv:2503.15475*, 2025.
- [11] G. Bradski. The OpenCV Library. *Dr. Dobb’s Journal of Software Tools*, 2000.

- [12] John Canny. A computational approach to edge detection. *IEEE TPAMI*, 8(6):679–698, 1986.
- [13] Xingyu Chen, Fu-Jen Chu, Pierre Gleize, Kevin J Liang, Alexander Sax, Hao Tang, Weiyao Wang, Michelle Guo, Thibaut Hardin, Xiang Li, Aohan Lin, Jiawei Liu, Ziqi Ma, Anushka Sagar, Bowen Song, Xiaodong Wang, Jianing Yang, Bowen Zhang, Piotr Dollár, Georgia Gkioxari, Matt Feiszli, and Jitendra Malik. SAM 3D: 3Dfy Anything in Images. arXiv:2511.16624, 2025.
- [14] Yen-Chi Cheng, Hsin-Ying Lee, Sergey Tulyakov, Alexander G Schwing, and Liang-Yan Gui. SDFusion: Multimodal 3d shape completion, reconstruction, and generation. In *CVPR*, pages 4456–4465, 2023.
- [15] Mehdi Cherti, Romain Beaumont, Ross Wightman, Mitchell Wortsman, Gabriel Ilharco, Cade Gordon, Christoph Schuhmann, Ludwig Schmidt, and Jenia Jitsev. Reproducible scaling laws for contrastive language-image learning. In *CVPR*, pages 2818–2829, 2023.
- [16] M. Cimpoi, S. Maji, I. Kokkinos, S. Mohamed, , and A. Vedaldi. Describing textures in the wild. In *CVPR*, 2014.
- [17] Kevin Clark, Minh-Thang Luong, Quoc V. Le, and Christopher D. Manning. ELECTRA: Pre-training text encoders as discriminators rather than generators. In *ICLR*, 2020.
- [18] Blender Online Community. *Blender - a 3D modelling and rendering package*. Blender Foundation, Stichting Blender Foundation, Amsterdam, 2018. URL <http://www.blender.org>.
- [19] Matt Deitke, Dustin Schwenk, Jordi Salvador, Luca Weihs, Oscar Michel, Eli VanderBilt, Ludwig Schmidt, Kiana Ehsani, Aniruddha Kembhavi, and Ali Farhadi. Objaverse: A universe of annotated 3d objects. In *CVPR*, pages 13142–13153, 2022.
- [20] Matt Deitke, Ruoshi Liu, Matthew Wallingford, Huong Ngo, Oscar Michel, Aditya Kusupati, Alan Fan, Christian Laforte, Vikram S. Voleti, Samir Yitzhak Gadre, Eli VanderBilt, Aniruddha Kembhavi, Carl Vondrick, Georgia Gkioxari, Kiana Ehsani, Ludwig Schmidt, and Ali Farhadi. Objaverse-xl: A universe of 10m+ 3d objects. In *NeurIPS*, 2023.
- [21] Matt Deitke, Christopher Clark, Sangho Lee, Rohun Tripathi, Yue Yang, Jae Sung Park, Mohammadreza Salehi, Niklas Muennighoff, Kyle Lo, Luca Soldaini, Jiasen Lu, Taira Anderson, Erin Bransom, Kiana Ehsani, Huong Ngo, YenSung Chen, Ajay Patel, Mark Yatskar, Christopher Callison-Burch, Andrew Head, Rose Hendrix, Favyen Bastani, Eli VanderBilt, Nathan Lambert, Yvonne Chou, Arnavi Chheda, Jenna Sparks, Sam Skjonsberg, Michael Schmitz, Aaron Sarnat, Byron Bischoff, Pete Walsh, Christopher Newell, Piper Wolters, Tanmay Gupta, Kuo-Hao Zeng, Jon Borchardt, Dirk Groeneveld, Jennifer Dumas, Crystal Nam, Sophie Lebrecht, Caitlin Marie Wittliff, Carissa Schoenick, Oscar Michel, Ranjay Krishna, Luca Weihs, Noah A. Smith, Hanna Hajishirzi, Ross Girshick, Ali Farhadi, and Aniruddha Kembhavi. Molmo and pixmo: Open weights and open data for state-of-the-art multimodal models. In *CVPR*, 2025.
- [22] Jiajun Deng, Tianyu He, Li Jiang, Tianyu Wang, Feras Dayoub, and Ian Reid. 3D-LLaVA: Towards generalist 3d lms with omni superpoint transformer. In *CVPR*, 2025.
- [23] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: Pre-training of deep bidirectional transformers for language understanding. In *North American Chapter of the Association for Computational Linguistics*, pages 4171–4186, 2019.
- [24] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, et al. An image is worth 16x16 words: Transformers for image recognition at scale. In *ICLR*, 2021.
- [25] Laura Downs, Anthony Francis, Nate Koenig, Brandon Kinman, Ryan Hickman, Krista Reymann, Thomas B McHugh, and Vincent Vanhoucke. Google scanned objects: A high-quality dataset of 3d scanned household items. In *International Conference on Robotics and Automation (ICRA)*, pages 2553–2560, 2022.
- [26] Aleksandr Dremov, Alexander Hägele, Atli Kosson, and Martin Jaggi. Training dynamics of the cooldown stage in warmup-stable-decay learning rate scheduler. *Transactions on Machine Learning Research*, 2025.
- [27] Mohamed El Banani, Amit Raj, Kevis-Kokitsi Maninis, Abhishek Kar, Yuanzhen Li, Michael Rubinstein, Deqing Sun, Leonidas Guibas, Justin Johnson, and Varun Jampani. Probing the 3D Awareness of Visual Foundation Models. In *CVPR*, 2024.
- [28] Patrick Esser, Robin Rombach, and Björn Ommer. Taming transformers for high-resolution image synthesis. In *CVPR*, 2021.

- [29] Yutong Feng, Yifan Feng, Haoxuan You, Xibin Zhao, and Yue Gao. MeshNet: Mesh Neural Network for 3D Shape Representation. In *AAAI*, 2019.
- [30] Rao Fu, Jingyu Liu, Xilun Chen, Yixin Nie, and Wenhan Xiong. Scene-LLM: Extending Language Model for 3D Visual Understanding and Reasoning, 2025.
- [31] Andreas Geiger, Philip Lenz, and Raquel Urtasun. Are we ready for autonomous driving? the kitti vision benchmark suite. In *CVPR*, pages 3354–3361, 2012.
- [32] Ankit Goyal, Hei Law, Bowei Liu, Alejandro Newell, and Jia Deng. Revisiting point cloud shape classification with a simple and effective baseline. In *ICML*, 2021.
- [33] Kaiming He, Georgia Gkioxari, Piotr Dollár, and Ross Girshick. Mask r-cnn. In *ICCV*, pages 2961–2969, 2017.
- [34] Dan Hendrycks and Kevin Gimpel. Gaussian error linear units (gelus). arXiv:1606.08415, 2016.
- [35] Alex Henry, Prudhvi Raj Dachapally, Shubham Shantaram Pawar, and Yuxuan Chen. Query-key normalization for transformers. In *Findings of the Association for Computational Linguistics: EMNLP*, pages 4246–4253, 2020.
- [36] Jonathan Ho, Ajay Jain, and Pieter Abbeel. Denoising diffusion probabilistic models. In *NeurIPS*, 2020.
- [37] Yicong Hong, Kai Zhang, Jiuxiang Gu, Sai Bi, Yang Zhou, Difan Liu, Feng Liu, Kalyan Sunkavalli, Trung Bui, and Hao Tan. LRM: Large reconstruction model for single image to 3d. In *ICLR*, 2024.
- [38] Yining Hong, Haoyu Zhen, Peihao Chen, Shuhong Zheng, Yilun Du, Zhenfang Chen, and Chuang Gan. 3d-llm: Injecting the 3d world into large language models. In *NeurIPS*, volume 36, pages 20482–20494, 2023.
- [39] Benran Hu, Junkai Huang, Yichen Liu, Yu-Wing Tai, and Chi-Keung Tang. Nerf-rpn: A general framework for object detection in nerfs. In *CVPR*, pages 23528–23538, 2023.
- [40] Edward J Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. LoRA: Low-rank adaptation of large language models. In *ICLR*, 2022.
- [41] Shengding Hu, Yuge Tu, Xu Han, Ganqu Cui, Chaoqun He, Weilin Zhao, Xiang Long, Zhi Zheng, Yewei Fang, Yuxiang Huang, Xinrong Zhang, Zhen Leng Thai, Chongyi Wang, Yuan Yao, Chenyang Zhao, Jie Zhou, Jie Cai, Zhongwu Zhai, Ning Ding, Chao Jia, Guoyang Zeng, dahai li, Zhiyuan Liu, and Maosong Sun. MiniCPM: Unveiling the potential of small language models with scalable training strategies. In *Conference on Language Modeling*, 2024.
- [42] Wenbo Hu, Xiangjun Gao, Xiaoyu Li, Sijie Zhao, Xiaodong Cun, Yong Zhang, Long Quan, and Ying Shan. Depthrafter: Generating consistent long depth sequences for open-world videos. In *CVPR*, 2025.
- [43] Guoxi Huang, Hongtao Fu, and Adrian G Bors. Masked image residual learning for scaling deeper vision transformers. *NeurIPS*, 36:57570–57582, 2023.
- [44] Jiangyong Huang, Silong Yong, Xiaojuan Ma, Xiongkun Linghu, Puhao Li, Yan Wang, Qing Li, Song-Chun Zhu, Baoxiong Jia, and Siyuan Huang. An embodied generalist agent in 3d world. In *ICML*, 2024.
- [45] Kuan-Chih Huang, Xiangtai Li, Lu Qi, Shuicheng Yan, and Ming-Hsuan Yang. Reason3d: Searching and reasoning 3d segmentation via large language model. *3DV*, 2025.
- [46] Siyuan Huang, Zan Wang, Puhao Li, Baoxiong Jia, Tengyu Liu, Yixin Zhu, Wei Liang, and Song-Chun Zhu. Diffusion-based generation, optimization, and planning in 3d scenes. In *CVPR*, pages 16750–16761, 2023.
- [47] Muhammad Zubair Irshad, Sergey Zakharov, Vitor Guizilini, Adrien Gaidon, Zsolt Kira, and Rares Ambrus. Nerf-mae: Masked autoencoders for self-supervised 3d representation learning for neural radiance fields. In *ECCV*, 2024.
- [48] Ayush Jain, Pushkal Katara, Nikolaos Gkanatsios, Adam W. Harley, Gabriel Sarch, Kriti Aggarwal, Vishrav Chaudhary, and Katerina Fragkiadaki. Odin: A single model for 2d and 3d segmentation. In *CVPR*, 2024.
- [49] Ayush Jain, Alexander Swerdlow, Yuzhou Wang, Sergio Arnaud, Ada Martin, Alexander Sax, Franziska Meier, and Katerina Fragkiadaki. Unifying 2d and 3d vision-language understanding. In *ICML*, 2025.

- [50] Hanwen Jiang, Shaowei Liu, Jiashun Wang, and Xiaolong Wang. Hand-object contact consistency reasoning for human grasps generation. In *ICCV*, pages 11107–11116, 2021.
- [51] Amrin Kareem, Jean Lahoud, and Hisham Cholakkal. PARIS3D: Reasoning-based 3d part segmentation using large multimodal model. In *ECCV*, 2024.
- [52] Bernhard Kerbl, Georgios Kopanas, Thomas Leimkuehler, and George Drettakis. 3d gaussian splatting for real-time radiance field rendering. *ACM Transactions on Graphics (TOG)*, 42(4):1–14, 2023.
- [53] Akshay Krishnan, Abhijit Kundu, Kevis-Kokitsi Maninis, James Hays, and Matthew Brown. OmniNOCS: A unified NOCS dataset and model for 3D lifting of 2D objects. In *ECCV*, 2024.
- [54] Duong H. Le, Tuan Pham, Sangho Lee, Christopher Clark, Aniruddha Kembhavi, Stephan Mandt, Ranjay Krishna, and Jiasen Lu. One diffusion to generate them all. In *CVPR*, 2025.
- [55] Vincent Leroy, Yohann Cabon, and Jerome Revaud. Grounding image matching in 3d with mast3r. In *ECCV*, 2024.
- [56] Jiahao Li, Hao Tan, Kai Zhang, Zexiang Xu, Fujun Luan, Yinghao Xu, Yicong Hong, Kalyan Sunkavalli, Greg Shakhnarovich, and Sai Bi. Instant3d: Fast text-to-3d with sparse-view generation and large reconstruction model. arXiv:2311.06214, 2023.
- [57] Junnan Li, Dongxu Li, Silvio Savarese, and Steven Hoi. BLIP-2: bootstrapping language-image pre-training with frozen image encoders and large language models. In *ICML*, 2023.
- [58] Puhao Li, Tengyu Liu, Yuyang Li, Yiran Geng, Yixin Zhu, Yaodong Yang, and Siyuan Huang. Gen-dexgrasp: Generalizable dexterous grasping. In *International Conference on Robotics and Automation (ICRA)*, pages 8068–8074, 2023.
- [59] Haotian Liu, Chunyuan Li, Qingyang Wu, and Yong Jae Lee. Visual instruction tuning. In *NeurIPS*, 2023.
- [60] Minghua Liu, Mikaela Angelina Uy, Donglai Xiang, Hao Su, Sanja Fidler, Nicholas Sharp, and Jun Gao. Partfield: Learning 3d feature fields for part segmentation and beyond. In *ICCV*, pages 9704–9715, 2025.
- [61] Ruoshi Liu, Rundi Wu, Basile Van Hoorick, Pavel Tokmakov, Sergey Zakharov, and Carl Vondrick. Zero-1-to-3: Zero-shot one image to 3d object. In *ICCV*, 2023.
- [62] William E. Lorensen and Harvey E. Cline. Marching cubes: A high resolution 3d surface construction algorithm. *SIGGRAPH Comput. Graph.*, 21(4):163–169, 1987.
- [63] Ilya Loshchilov and Frank Hutter. Decoupled weight decay regularization. arXiv:1711.05101, 2017.
- [64] Jiasen Lu, Christopher Clark, Sangho Lee, Zichen Zhang, Savva Khosla, Ryan Marten, Derek Hoiem, and Aniruddha Kembhavi. Unified-IO 2: Scaling autoregressive multimodal models with vision, language, audio, and action. arXiv:2312.17172, 2023.
- [65] Jiasen Lu, Christopher Clark, Rowan Zellers, Roozbeh Mottaghi, and Aniruddha Kembhavi. UNIFIED-IO: A unified model for vision, language, and multi-modal tasks. In *ICLR*, 2023.
- [66] Jiaxin Lu, Hao Kang, Haoxiang Li, Bo Liu, Yiding Yang, Qixing Huang, and Gang Hua. Ugg: Unified generative grasping. In *ECCV*, 2024.
- [67] Tiange Luo, Chris Rockwell, Honglak Lee, and Justin Johnson. Scalable 3d captioning with pretrained models. *Advances in Neural Information Processing Systems*, 36:75307–75337, 2023.
- [68] Tiange Luo, Justin Johnson, and Honglak Lee. View selection for 3d captioning via diffusion ranking. In *European Conference on Computer Vision*, pages 180–197. Springer, 2024.
- [69] Viktor Makoviychuk, Lukasz Wawrzyniak, Yunrong Guo, Michelle Lu, Kier Storey, Miles Macklin, David Hoeller, Nikita Rudin, Arthur Allshire, Ankur Handa, and Gavriel State. Isaac gym: High performance GPU based physics simulation for robot learning. In *NeurIPS*, 2021.
- [70] Rayhane Mama, Marc S Tyndel, Hashiam Kadhim, Cole Clifford, and Ragavan Thurairatnam. Nwt: towards natural audio-to-video generation with representation learning. arXiv:2106.04283, 2021.
- [71] Ben Mildenhall, Pratul P. Srinivasan, Matthew Tancik, Jonathan T. Barron, Ravi Ramamoorthi, and Ren Ng. Nerf: Representing scenes as neural radiance fields for view synthesis. In *ECCV*, 2020.
- [72] David Mizrahi, Roman Bachmann, Oğuzhan Fatih Kar, Teresa Yeo, Mingfei Gao, Afshin Dehghan, and Amir Zamir. 4M: Massively multimodal masked modeling. In *NeurIPS*, 2023.

- [73] Vishal Nedungadi, Ankit Karirya, Stefan Oehmcke, Serge Belongie, Christian Igel, and Nico Lang. Mmearth: Exploring multi-modal pretext tasks for geospatial representation learning. In *European Conference on Computer Vision*, pages 164–182. Springer, 2024.
- [74] OpenAI. GPT-4V(ision) System Card, 2023. URL https://cdn.openai.com/papers/GPTV_System_Card.pdf.
- [75] Maxime Oquab, Timothée Darcet, Théo Moutakanni, Huy V. Vo, Marc Szafraniec, Vasil Khalidov, Pierre Fernandez, Daniel HAZIZA, Francisco Massa, Alaaeldin El-Nouby, Mido Assran, Nicolas Ballas, Wojciech Galuba, Russell Howes, Po-Yao Huang, Shang-Wen Li, Ishan Misra, Michael Rabbat, Vasu Sharma, Gabriel Synnaeve, Hu Xu, Herve Jegou, Julien Mairal, Patrick Labatut, Armand Joulin, and Piotr Bojanowski. DINOv2: Learning robust visual features without supervision. *Transactions on Machine Learning Research*, 2024. ISSN 2835-8856.
- [76] Jiachuan Peng, Marcel Beetz, Abhirup Banerjee, Min Chen, and Vicente Grau. Aem: An interpretable multi-task multi-modal framework for cardiac disease prediction. *Medical Image Analysis*, 109:103951, 2026. ISSN 1361-8415. doi: <https://doi.org/10.1016/j.media.2026.103951>. URL <https://www.sciencedirect.com/science/article/pii/S1361841526000204>.
- [77] Julius Plücker. *Analytisch-geometrische Entwicklungen*, volume 1. GD Baedeker, 1828.
- [78] Charles R Qi, Hao Su, Kaichun Mo, and Leonidas J Guibas. Pointnet: Deep learning on point sets for 3d classification and segmentation. In *CVPR*, 2017.
- [79] Charles Ruizhongtai Qi, Li Yi, Hao Su, and Leonidas J Guibas. PointNet++: Deep hierarchical feature learning on point sets in a metric space. In *NeurIPS*, 2017.
- [80] Zekun Qi, Runpei Dong, Shaochen Zhang, Haoran Geng, Chunrui Han, Zheng Ge, Li Yi, and Kaisheng Ma. ShapeLLM: Universal 3D Object Understanding for Embodied Interaction. In *ECCV*, 2024.
- [81] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. Learning transferable visual models from natural language supervision. In *ICML*, pages 8748–8763, 2021.
- [82] Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J Liu. Exploring the limits of transfer learning with a unified text-to-text transformer. *Journal of machine learning research*, 21(140):1–67, 2020.
- [83] Scott Reed, Konrad Zolna, Emilio Parisotto, Sergio Gómez Colmenarejo, Alexander Novikov, Gabriel Barth-maroon, Mai Giménez, Yury Sulsky, Jackie Kay, Jost Tobias Springenberg, Tom Eccles, Jake Bruce, Ali Razavi, Ashley Edwards, Nicolas Heess, Yutian Chen, Raia Hadsell, Oriol Vinyals, Mahyar Bordbar, and Nando de Freitas. A generalist agent. *Transactions on Machine Learning Research*, 2022.
- [84] Jiawei Ren, Liang Pan, , and Ziwei Liu. Benchmarking and analyzing point cloud classification under corruptions. In *ICML*, 2022.
- [85] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation. In *International Conference on Medical image computing and computer-assisted intervention*, pages 234–241. Springer, 2015.
- [86] Aadarsh Sahoo, Vansh Tibrewal, and Georgia Gkioxari. Aligning text, images, and 3d structure token-by-token. arXiv:2506.08002, 2025.
- [87] Noam Shazeer. Glu variants improve transformer. arXiv:2002.05202, 2020.
- [88] Jie Shi, Chenfei Wu, Jian Liang, Xiang Liu, and Nan Duan. DiVAE: Photorealistic images synthesis with denoising diffusion decoder. arXiv:2206.00386, 2022.
- [89] Linda B. Smith and Michael Gasser. The development of embodied cognition: Six lessons from babies. *Artificial Life*, 11:13–29, 2005.
- [90] Siddharth Srivastava and Gaurav Sharma. Omnivec2-a novel transformer based network for large scale multimodal and multitask learning. In *CVPR*, pages 27412–27424, 2024.
- [91] Pei Sun, Henrik Kretzschmar, Xerxes Dotiwalla, Aurelien Chouard, Vijaysai Patnaik, Paul Tsui, James Guo, Yin Zhou, Yuning Chai, Benjamin Caine, Vijay Vasudevan, Wei Han, Jiquan Ngiam, Hang Zhao, Aleksei Timofeev, Scott Ettinger, Maxim Krivokon, Amy Gao, Aditya Joshi, Yu Zhang, Jonathon Shlens, Zhifeng Chen, and Dragomir Anguelov. Scalability in perception for autonomous driving: Waymo open dataset. In *CVPR*, 2020.

- [92] Wenfang Sun, Xinyuan Song, Pengxiang Li, Lu Yin, Yefeng Zheng, and Shiwei Liu. The curse of depth in large language models. *arXiv:2502.05795*, 2025.
- [93] Zhenyu Tang, Junwu Zhang, Xinhua Cheng, Wangbo Yu, Chaoran Feng, Yatian Pang, Bin Lin, and Li Yuan. Cycle3d: High-quality and consistent image-to-3d generation via generation-reconstruction cycle. In *AAAI*, 2025.
- [94] Yi Tay, Mostafa Dehghani, Jinfeng Rao, William Fedus, Samira Abnar, Hyung Won Chung, Sharan Narang, Dani Yogatama, Ashish Vaswani, and Donald Metzler. Scale efficiently: Insights from pre-training and fine-tuning transformers. *arXiv:2109.10686*, 2021.
- [95] Tencent Hunyuan3D Team. Hunyuan3d-omni: A unified framework for controllable generation of 3d assets. *arXiv:2509.21245*, 2025.
- [96] Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. Llama 2: Open foundation and fine-tuned chat models. *arXiv:2307.09288*, 2023.
- [97] Du Tran, Lubomir Bourdev, Rob Fergus, Lorenzo Torresani, and Manohar Paluri. Learning spatiotemporal features with 3d convolutional networks. In *ICCV*, pages 4489–4497, 2015.
- [98] Aaron Van Den Oord, Oriol Vinyals, et al. Neural discrete representation learning. In *NeurIPS*, 2017.
- [99] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. In *NeurIPS*, volume 30, 2017.
- [100] He Wang, Srinath Sridhar, Jingwei Huang, Julien Valentin, Shuran Song, and Leonidas J. Guibas. Normalized object coordinate space for category-level 6d object pose and size estimation. In *CVPR*, 2019.
- [101] Jianyuan Wang, Minghao Chen, Nikita Karaev, Andrea Vedaldi, Christian Rupprecht, and David Novotny. Vggt: Visual geometry grounded transformer. In *CVPR*, 2025.
- [102] Peng Wang, An Yang, Rui Men, Junyang Lin, Shuai Bai, Zhikang Li, Jianxin Ma, Chang Zhou, Jingren Zhou, and Hongxia Yang. Ofa: Unifying architectures, tasks, and modalities through a simple sequence-to-sequence learning framework. In *ICML*, 2022.
- [103] Shuzhe Wang, Vincent Leroy, Yohann Cabon, Boris Chidlovskii, and Jerome Revaud. Dust3r: Geometric 3d vision made easy. In *CVPR*, 2024.
- [104] Xi Wang and Laurence Aitchison. How to set adamw’s weight decay as you scale model and dataset size. *arXiv:2405.13698*, 2024.
- [105] Yue Wang, Yongbin Sun, Ziwei Liu, Sanjay E Sarma, Michael M Bronstein, and Justin M Solomon. Dynamic graph cnn for learning on point clouds. In *ACM Transactions on Graphics*, 2019.
- [106] Zehan Wang, Ziang Zhang, Hang Zhang, Luping Liu, Rongjie Huang, Xize Cheng, Hengshuang Zhao, and Zhou Zhao. Omnibind: Large-scale omni multimodal representation via binding spaces. In *ICLR*, 2025.
- [107] Shuhei Watanabe. Tree-structured Parzen estimator: Understanding its algorithm components and their roles for better empirical performance. *arXiv:2304.11127*, 2023.
- [108] Hao Wen, Zehuan Huang, Yaohui Wang, Xinyuan Chen, Yu Qiao, and Lu Sheng. Ouroboros3D: Image-to-3d generation via 3d-aware recursive diffusion. In *CVPR*, 2025.
- [109] Xiaoyang Wu, Li Jiang, Peng-Shuai Wang, Zhijian Liu, Xihui Liu, Yu Qiao, Wanli Ouyang, Tong He, and Hengshuang Zhao. Point transformer v3: Simpler, faster, stronger. In *CVPR*, 2024.
- [110] Yilan Wu, Bo Qian, Tingyao Li, Yiming Qin, Zhouyu Guan, Tingli Chen, Yali Jia, Ping Zhang, Dian Zeng, Sayoko Moroi, et al. An eyecare foundation model for clinical assistance: a randomized controlled trial. *Nature medicine*, 31(10):3404–3413, 2025.
- [111] Zhirong Wu, Shuran Song, Aditya Khosla, Fisher Yu, Linguang Zhang, Xiaoou Tang, and Jianxiong Xiao. 3D ShapeNets: A Deep Representation for Volumetric Shapes. In *CVPR*, 2015.
- [112] Jianfeng Xiang, Zelong Lv, Sicheng Xu, Yu Deng, Ruicheng Wang, Bowen Zhang, Dong Chen, Xin Tong, and Jiaolong Yang. Structured 3d latents for scalable and versatile 3d generation. In *CVPR*, pages 21469–21480, 2025.

- [113] Tiange Xiang, Chaoyi Zhang, Yang Song, Jianhui Yu, and Weidong Cai. Walk in the cloud: Learning curves for point clouds shape analysis. In *ICCV*, 2021.
- [114] Jinheng Xie, Weijia Mao, Zechen Bai, David Junhao Zhang, Weihao Wang, Kevin Qinghong Lin, Yuchao Gu, Zhijie Chen, Zhenheng Yang, and Mike Zheng Shou. Show-o: One single transformer to unify multimodal understanding and generation. In *ICLR*, 2025.
- [115] Jinheng Xie, Zhenheng Yang, and Mike Zheng Shou. Show-o2: Improved native unified multimodal models. In *NeurIPS*, 2025.
- [116] Mutian Xu, Junhao Zhang, Zhipeng Zhou, Mingye Xu, Xiaojuan Qi, and Yu Qiao. Learning geometry-disentangled representation for complementary understanding of 3d object point cloud. In *AAAI*, 2021.
- [117] Yinzhen Xu, Weikang Wan, Jialiang Zhang, Haoran Liu, Zikang Shan, Hao Shen, Ruicheng Wang, Haoran Geng, Yijia Weng, Jiayi Chen, et al. Unidexgrasp: Universal robotic dexterous grasping via learning diverse proposal generation and goal-conditioned policy. In *CVPR*, pages 4737–4746, 2023.
- [118] Le Xue, Mingfei Gao, Chen Xing, Roberto Martín-Martín, Jiajun Wu, Caiming Xiong, Ran Xu, Juan Carlos Niebles, and Silvio Savarese. ULIP: Learning a unified representation of language, images, and point clouds for 3d understanding. In *CVPR*, 2023.
- [119] Le Xue, Ning Yu, Shu Zhang, Artemis Panagopoulou, Junnan Li, Roberto Martín-Martín, Jiajun Wu, Caiming Xiong, Ran Xu, Juan Carlos Niebles, et al. ULIP-2: Towards scalable multimodal pre-training for 3d understanding. In *CVPR*, pages 27091–27101, 2024.
- [120] Ge Yang, Edward Hu, Igor Babuschkin, Szymon Sidor, Xiaodong Liu, David Farhi, Nick Ryder, Jakub Pachocki, Weizhu Chen, and Jianfeng Gao. Tuning large neural networks via zero-shot hyperparameter transfer. *NeurIPS*, 34:17084–17097, 2021.
- [121] Lihe Yang, Bingyi Kang, Zilong Huang, Xiaogang Xu, Jiashi Feng, and Hengshuang Zhao. Depth anything: Unleashing the power of large-scale unlabeled data. In *CVPR*, 2024.
- [122] Junliang Ye, Zhengyi Wang, Ruowen Zhao, Shenghao Xie, and Jun Zhu. ShapeLLM-omni: A native multimodal LLM for 3d generation and understanding. In *NeurIPS*, 2025.
- [123] Ed Yong. *An Immense World: How Animal Senses Reveal the Hidden Realms Around Us*. Random House, New York, 2022. ISBN 978-0593133231. URL <https://www.penguinrandomhouse.com/books/616914/an-immense-world-by-ed-yong/>.
- [124] Xumin Yu, Lulu Tang, Yongming Rao, Tiejun Huang, Jie Zhou, and Jiwen Lu. Point-bert: Pre-training 3d point cloud transformers with masked point modeling. In *CVPR*, 2022.
- [125] Jason Y Zhang, Amy Lin, Moneish Kumar, Tzu-Hsuan Yang, Deva Ramanan, and Shubham Tulsiani. Cameras as rays: Pose estimation via ray diffusion. In *ICLR*, 2024.
- [126] Longwen Zhang, Ziyu Wang, Qixuan Zhang, Qiwei Qiu, Anqi Pang, Haoran Jiang, Wei Yang, Lan Xu, and Jingyi Yu. Clay: A controllable large-scale generative model for creating high-quality 3d assets. *ACM Transactions on Graphics (TOG)*, 43(4):1–20, 2024.
- [127] Yumin Zhang, Xingyu Miao, Haoran Duan, Bo Wei, Tejal Shah, Yang Long, and Rajiv Ranjan. Exactdreamer: High-fidelity text-to-3d content creation via exact score matching. *arXiv preprint arXiv:2405.15914*, 2024.
- [128] Zhihao Zhang, Shengcao Cao, and Yu-Xiong Wang. TAMM: Triadapter multi-modal learning for 3d shape understanding. In *CVPR*, 2024.
- [129] Hengshuang Zhao, Li Jiang, Jiaya Jia, Philip HS Torr, and Vladlen Koltun. Point transformer. In *ICCV*, pages 16259–16268, 2021.
- [130] Yiming Zhong, Qi Jiang, Jingyi Yu, and Yuexin Ma. Dexgrasp anything: Towards universal robotic dexterous grasping with physics awareness. In *CVPR*, 2025.
- [131] Gaoyue Zhou, Hengkai Pan, Yann Lecun, and Lerrel Pinto. DINO-WM: World models on pre-trained visual features enable zero-shot planning. In *ICML*, volume 267, pages 79115–79135, 2025.
- [132] Qian-Yi Zhou, Jaesik Park, and Vladlen Koltun. Open3D: A modern library for 3D data processing. *arXiv:1801.09847*, 2018.
- [133] Chenming Zhu, Tai Wang, Wenwei Zhang, Jiangmiao Pang, and Xihui Liu. Llava-3d: A simple yet effective pathway to empowering llms with 3d-awareness. In *ICCV*, 2025.

Appendix

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Additional experiments

For calculating metrics, we firstly align the predicted objects with the ground truth as they are not aligned for all methods. We then render the predicted and ground-truth 3D objects on both white and black backgrounds and compute metrics for each background subset separately. We do this because we observe differences in the metrics due to background color, potentially stemming from dataset statistics and model biases. As indicated in Sec. B.1, we train OmniDiMM with black backgrounds for the conditioning images, which may explain its improved performance under the black-background evaluation. However, because no comparable information is available for the baselines, we report both settings to account for background color as a potential confounder that could drop the performance of the compared methods. We calculate each metric using six renders of each object, obtained with the same view-sampling technique used for Novel View Synthesis (NVS) and described in Sec. 5.1, to ensure that the predictions are consistent from all directions. Qualitative comparison between OmniDiMM and the novel view synthesis baselines, Ouroboros [108] and Zero123 [61], Fig. 12 shows that the OmniDiMM performs better than the baselines when preserving the geometry and consistency with the provided input image.



Figure 12: **Qualitative comparison of novel-view synthesis.** Our model outperforms previous approaches in both novel view synthesis and 3D generation from a single view. In particular, our model greatly outperforms other methods when given challenging views that include a high degree of ambiguity and self-occlusions, maintaining geometric coherence across generated target views. We compare with Zero123 [61] and Ouroboros [108] as they allow for generation at arbitrary relative poses.

Qualitative comparisons between OmniDiMM and the baselines, SAM3D [13] and Trellis [112], in Fig. 7 show that OmniDiMM remains more faithful to the input geometry and produces more consistent outputs, while the baselines often struggle with shape and color fidelity. Fig. 13 shows the qualitative improvement in performance of 3DGS generations by leveraging intermediate generations via chaining.

We provide additional qualitative examples of any-to-any generation in Figs. 15 and 16.

Steerable Text-Conditioned Generation

As OmniDiMM is an any-to-any model, we also demonstrate its ability to generate 2D images and 3D objects from text alone, as well using text as a steering signal alongside other modalities such as 2D masks. Figure 14 shows examples of 2D image and 3DGS generation from text. Similar to the results for novel-view synthesis and 3D generation, we find that chaining through DINOv2 [75] and CLIP [81] feature maps yields substantially higher-quality results.

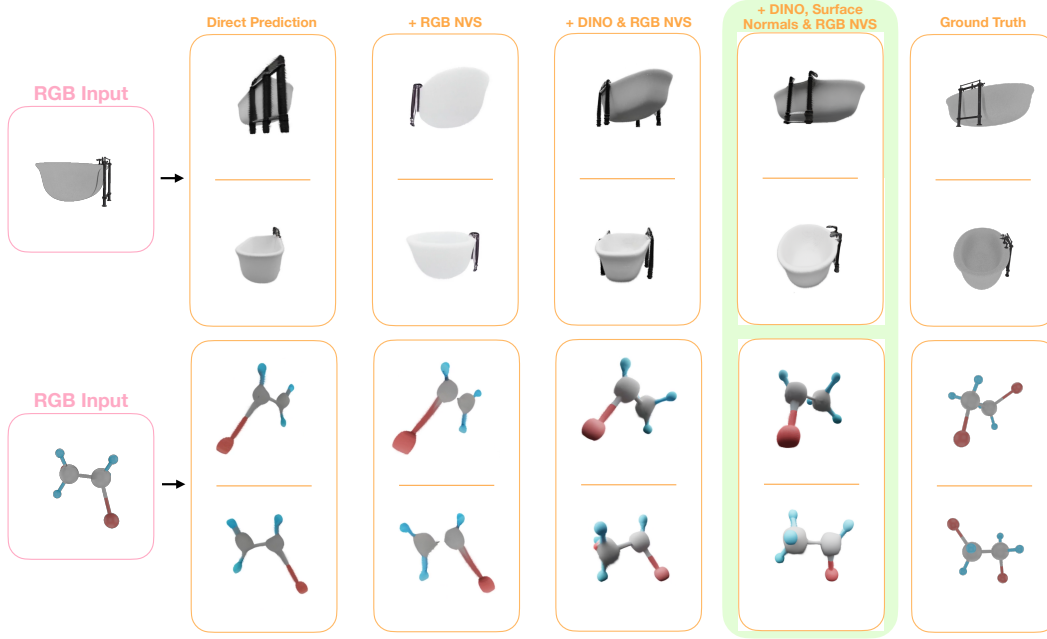


Figure 13: **Qualitative ablation of chaining during prediction.** For 3D generation, we find that leveraging the any-to-any prediction capabilities of OmniDiMM by first generating six diverse novel views of the object and then using them to produce the final 3DGS output significantly outperforms direct 3D generation from a single image. The outputs obtained via chaining contain sharper, finer details and produce more accurate geometries than direct predictions.

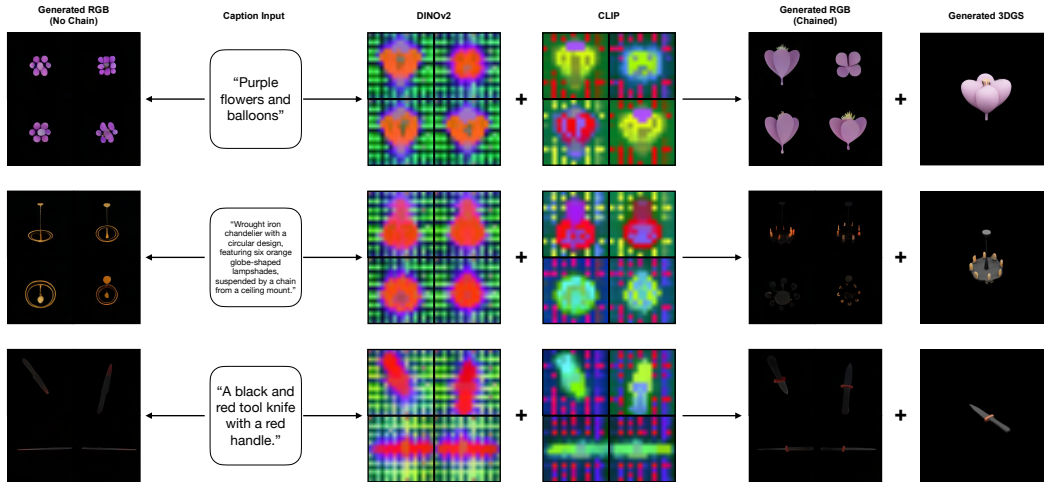


Figure 14: OmniDiMM can generate RGB and 3DGS from text when chained through dense DINOv2 [75] and CLIP [81] feature maps.

Input		Predictions													
		RGB	Depth	Normals	Edges	Mask	DINOv2	CLIP	Mesh	Voxel	UDF	Grid	NeRF	Partfield	MV
RGB															
Depth															
Normals															
Edges															
Mask															
DINOv2															
CLIP															
Mesh															
Voxel															
UDF															
Grid															
NeRF															
Partfield															

Figure 15: **Additional any-to-any generation.** OmniDiMM can generate all modalities from a single input with a high degree of cross-modal consistency.

Input		Predictions													
		RGB	Depth	Normals	Edges	Mask	DINOv2	CLIP	Mesh	Voxel	UDF	Grid	NeRF	Partfield	MV
RGB	→														
Depth	→														
Normals	→														
Edges	→														
Mask	→														
DINOv2	→														
CLIP	→														
Mesh	→														
Voxel	→														
UDF	→														
Grid	→														
NeRF	→														
Partfield	→														

Figure 16: **Additional any-to-any generation.** OmniDiMM can generate all modalities from a single input with a high degree of cross-modal consistency.

A Pseudolabeling Pipeline and Modality Selection

A.1 Dataset Source

We construct an aligned dataset spanning 1D, 2D, and 3D modalities using assets from Objaverse-XL [20]. Objaverse-XL is a large-scale dataset of objects collected from five data sources, consisting primarily of indexed 3D assets from public GitHub repositories, as well as objects from Thingiverse, Sketchfab, Polycam, and the Smithsonian Institution. After deduplication and filtering for compatibility with Blender [18] rendering, these assets yield 10 million objects. Given the inherent noise in this large-scale crawled dataset, we pretrain OmniDiMM on the Cap3D subset [67], a curated collection of 1.6 million assets from Objaverse-XL that includes approximately 780k objects from Objaverse v1.0 [19], along with objects from Sketchfab and GitHub filtered using quality proxy estimates [20]. Using Cap3D provides two key advantages: it enables pretraining on higher-quality data and provides existing captions generated via the pseudo-labeling procedure of DiffuRank [68]. We further filter the Cap3D subset to ensure compatibility with the modality derivation pipelines for all considered modalities, resulting in a final dataset of 972k objects.

We use textured object meshes as a ‘grounding’ modality: a canonical representation from which all other modalities are derived. In prior 1D and 2D works such as 4M [72, 7], images and text serve this role, with additional modalities obtained using expert models (*e.g.*, depth or normal estimators). For explicit 3D data, representations such as voxels, point clouds, and meshes are fundamentally linked through classical geometric transformations. We select meshes because they offer the highest geometric fidelity, providing a rich, continuous surface representation from which other discrete 3D formats can be accurately extracted. Furthermore, meshes are the most abundant textured 3D representation that supports dense, hole-free rendering. This allows us to directly synthesize high-quality 2D modalities, such as multi-view RGB, which can subsequently be used to derive additional modalities. Together, these properties make textured meshes the ideal ‘grounding’ modality for our dataset.

A.2 Object Captioning

Joint training with captions enables generation from text, steerable conditioning and captioning for any multi-view 2D modality or 3D modality supported by OmniDiMM. As mentioned in Sec. A.1, we use the captions from Cap3D [67], which are generated by first rendering multiple views of an object and captioning them with BLIP-2 [57]. Next, DiffuRank [68] evaluates and ranks these view-dependent captions to identify the most informative perspectives. Finally, GPT-4V [74] synthesizes the top-ranked views into a global caption for the 3D asset.

A.3 Modality List

The complete set of modalities that we use to train OmniDiMM is:

- | | |
|-----------------------------------|-----------------------------|
| 1. Raw RGB (non-tokenized) | 10. Text (captions) |
| 2. RGB | 11. Mesh geometry |
| 3. Depth | 12. Voxels |
| 4. Surface normals | 13. UDFs |
| 5. Masks | 14. 3DGSs [52] |
| 6. Canny edges [12] | 15. NeRF weights [39] |
| 7. Global DINOv2 features [75] | 16. NeRF grids [39] |
| 8. Dense DINOv2 feature maps [75] | 17. Part features [60] |
| 9. Dense CLIP feature maps [81] | 18. ULIP-2 embeddings [119] |

A.4 2D Modalities

RGB, Depth, Normals & Masks: We include RGB for standard multi-view 2D compatibility and masks to enable foreground-background separation. We also incorporate depth and surface normals as standard 2.5D modalities that bridge 2D and 3D representations. We render these four modalities directly from object meshes in Blender using the *EEVEE* render engine. We center and normalize the input meshes to fit within a unit sphere and set up uniform lighting with a cube of area lights surrounding the object. For each object, we render 20 distinct views from a bounding sphere of radius 2. To ensure broad spatial coverage, camera positions are selected using Farthest Point Sampling (FPS): each subsequent view is chosen from 30 random candidates to maximize the geometric distance from all previously selected views. Each camera is placed at the sampled position and oriented toward the origin. We render all images at a resolution of 512^2 with a field of view of 60° . Because OmniDiMM processes multiple views across numerous modalities, the sequence length scales linearly with the number of inputs and quadratically with spatial resolution, easily exceeding tens of thousands of tokens per forward pass. To control this combinatorial growth and maintain a tractable joint token sequence during pretraining, we downsample these renders to 224^2 before tokenization. In total, we generate 19.4 million renders per modality for pretraining.

Raw RGB: While raw RGB captures the same underlying visual information as its tokenized counterpart, it bypasses the reconstruction bottleneck of discrete tokenizers, facilitates continuous end-to-end fine-tuning, and has been shown to improve transfer results [72, 7]. To bridge the domain gap with real-world scenes, we augment the rendered RGB images by alpha-blending them with random backgrounds from the Describable Textures Dataset [16]. To simulate realistic multi-view environment correlations, we apply the same background texture across all views of a given object with a 50% probability; otherwise, backgrounds are sampled independently per view. In all cases, we apply random resized cropping with scale factors ranging from 0.5 to 1.0.

Canny Edges: We incorporate Canny edges [12] to enable generation from low-detail inputs such as shapes and sketches. We compute them from the RGB renders using OpenCV [11], with low and high hysteresis thresholds of 100 and 200, respectively.

2D Feature Modalities: We include global DINOv2 embeddings [75] as a modality to support diverse downstream applications, such as multimodal retrieval. We also incorporate dense DINOv2 [75] and CLIP [81] feature maps, which can serve as chaining modalities to improve generation quality. We extract DINOv2 features using the DINOv2-B14 model, deriving the global feature from the [CLS] token and the dense feature maps from the corresponding image patch tokens. We extract a distinct global feature for each rendered view rather than computing a single aggregated object-level embedding. Because 2D projections of a 3D object vary substantially with camera pose, the corresponding embeddings are highly view-dependent. We verified this empirically through cross-retrieval tests on multi-view samples: although adjacent camera angles generally yield similar embeddings, disparate views often exhibit little apparent similarity. Consequently, naively averaging these view-specific features would produce a collapsed, uninformative representation. For CLIP feature maps, we use the pretrained CLIP-B16 model, extracting image features obtained from the final transformer layer and applying the final layer normalization.

A.5 3D Modalities

Voxels & UDFs: Voxels indicate the occupancy status of locations in 3D space and provide a coarse representation of an object’s geometry, which can be used to generate detailed 3D models from weak conditioning. UDFs encode the minimum distance from a point to the object’s mesh surface, providing a detailed, dense description of geometry that can be readily extracted from various 3D representations such as meshes and point clouds. We generate these modalities from object meshes using Open3D [132]. We determine filled voxels by identifying all voxels that intersect a mesh triangle at a resolution of 32^3 . We compute UDFs by ray casting on a dense 3D grid with a resolution of 64^3 .

3DGSs: 3DGSs are a modern, high-fidelity textured 3D representation that enables high-quality image rendering via rasterization and conversion to meshes through algorithms such as marching cubes [62]. To include 3DGSs as a modality, we use Trellis SLATs [112], which decode to Gaussian splats. These SLATs form a sparse representation of the object and are obtained by training a VAE to predict Gaussian splats from multi-view inputs.

To obtain the SLATs for each object, we follow the procedure of Xiang *et al.* [112]. We capture 100 uniformly sampled images for each object and extract DINOv2 feature maps from them. We derive a surface voxel structure at a resolution of 64^3 from the mesh and then project the multi-view average of the DINOv2 feature maps onto the surface voxels. Finally, we encode the augmented voxels with a sparse VAE to obtain the final SLATs, which we use as the representation for 3DGSs.

NeRF Weights: NeRFs are another recent, high-quality 3D representation commonly used besides 3DGSs. They enable rendering novel views of an object by predicting a 3D RGB and density field defined in all points in space that used in the rendering equation. However, NeRFs are typically trained separately for each object, making their derivation challenging and unscalable at the scale of our pretraining dataset. In addition, it is unclear how learnable the resulting space of independently trained NeRFs would be. Instead, we re-implement the generalizable NeRF model Instant3D [56], which predicts a set of triplane features for each object that a shared MLP decodes into RGB values and densities at any point in space. We therefore treat these triplanes as equivalent to the weights of a NeRF for a given object and use them as our NeRF weight modality. Each triplane consists of three planes with a resolution of 64^2 .

NeRF Grids: Prior work has shown that discretizing the color and density fields predicted by NeRFs yields an effective 3D modality [39, 47]. This provides an explicit spatial description of textured appearance, making it a useful representation. To obtain these grids, we use the aforementioned triplanes and decode them with the shared MLP. Then, for each point in a grid with resolution 64^3 , we query the corresponding RGB and density values. Note that, while NeRF weights can be interpreted as the 3D analogue of feature maps, NeRF grids are closer to voxels. Despite some redundancy in how these modalities are obtained, the way information is structured in the two representations differs, and so do the resulting tokens.

Part Features: Parts in 3D are often ill-defined and task-specific, with meaningful decompositions existing at different levels of specificity depending on the context. Therefore, instead of learning a fixed level of part segmentation granularity, we learn a part feature field that can be decoded at different levels of part complexity. We use PartField [60] to derive these part features. We sample 100,000 points per object, which the PartField model transforms into part triplanes with a resolution of 128^2 . We use this triplane as our part feature modality.

This triplane can be sampled at any point in 3D space to obtain the corresponding part feature, similar to a NeRFs triplane. We visualize part features for a model by querying points on the surface of the ground-truth mesh to form a point cloud and, for each point, querying the triplane for the corresponding part feature. We then reduce the dimensionality of these features to 3 using PCA to obtain a color for each point. To extract parts from the part features, we cluster them using a method such as k -means, thereby partitioning an object into k parts. This enables us to control the complexity and granularity of the extracted parts through the clustering method and the choice of level.

ULIP-2 Embeddings: We include a global representation of each object by using its ULIP-2 [119] embedding as a modality. ULIP-2 aligns features for a 3D object, extracted with a Point-BERT [124] model, with pretrained CLIP [81] image-text features. As such, the ULIP-2 embedding is aligned with the underlying object’s 2D renders and text caption, providing a global semantic feature. ULIP-2 embeddings can be used for purposes similar to those of CLIP embeddings, namely matching 3D models to images and text through feature similarity or performing 3D retrieval.

To extract ULIP-2 embeddings, we randomly sample 8,192 colored points from the surface of each object and process them with ULIP-2’s Point-BERT [124] encoder, which is aligned with OpenCLIP (ViT-G/14) [15].

B Tokenizer Training Details

B.1 1D & 2D Tokenization

To tokenize multi-view 2D modalities, we apply pretrained 2D tokenizers to each view separately. View locations are then disambiguated within the model using positional embeddings rather than being handled by the tokenizers.

RGB and Depth: We use the COSMOS discrete image tokenizer [1] with a patch size of 16. To match how COSMOS handles transparent images, we replace the background of the RGB object

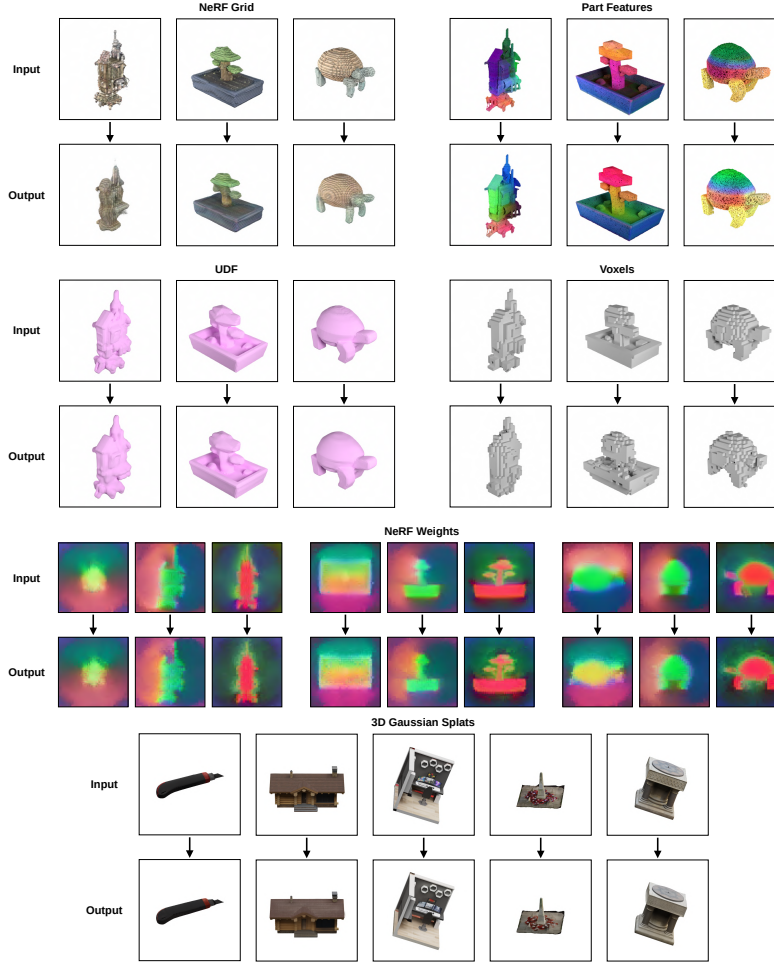


Figure 17: **Qualitative results of our novel tokenizers.** We train a set of tokenizers for 3D modalities that have not previously been tokenized. Our tokenizers reconstruct full 3D models from a small number of discrete tokens, successfully recovering geometry, texture, and semantics.

renders with a solid black background via alpha blending before tokenization. We clip the rendered metric depth to $z_{raw} \in [1, 3]$, which corresponds to the maximal depth range in our rendering setup given the unit-sphere mesh normalization and fixed camera distance. We then normalize these clipped values to $z_{norm} \in [\epsilon, 1]$, with $\epsilon = 10^{-6}$. Given the inherent domain gap between relative depth estimated from real-world images and our rendered metric depth, the pretrained 4M [72] depth encoder is unsuitable out of the box. We evaluated two fine-tuning strategies for the 4M encoder. First, we applied standard depth processing with a SmoothL1 reconstruction loss (Fig. 18c), which yielded overly smooth foregrounds lacking high-frequency detail. This over-smoothing occurs because our rendered depth values are heavily concentrated at the maximum value, corresponding to the background. To mitigate this imbalance and encourage higher-fidelity foreground representations, we upweighted the foreground prediction penalty by a factor of 10 relative to the background (Fig. 18d) and used a truncated version of the SmoothL1 loss to account for the clipping of predicted values. Despite this, predictions on novel instances remained biased toward lower values, as evident at the nearest point of the faucet. Alternatively, we tested the COSMOS tokenizer [1] directly on normalized depth values to mimic the dynamic range of natural images (Fig. 18e); however, this resulted in persistent reconstruction artifacts across samples.

Following common practice in depth estimation [121, 42], we instead invert the normalized depth values to obtain disparity ($z_{norm} \in [\epsilon, 1] \rightarrow d \in [1, \frac{1}{\epsilon}]$). Using disparity instead of normalized metric depth expands the numerical resolution of the foreground and compresses the empty back-

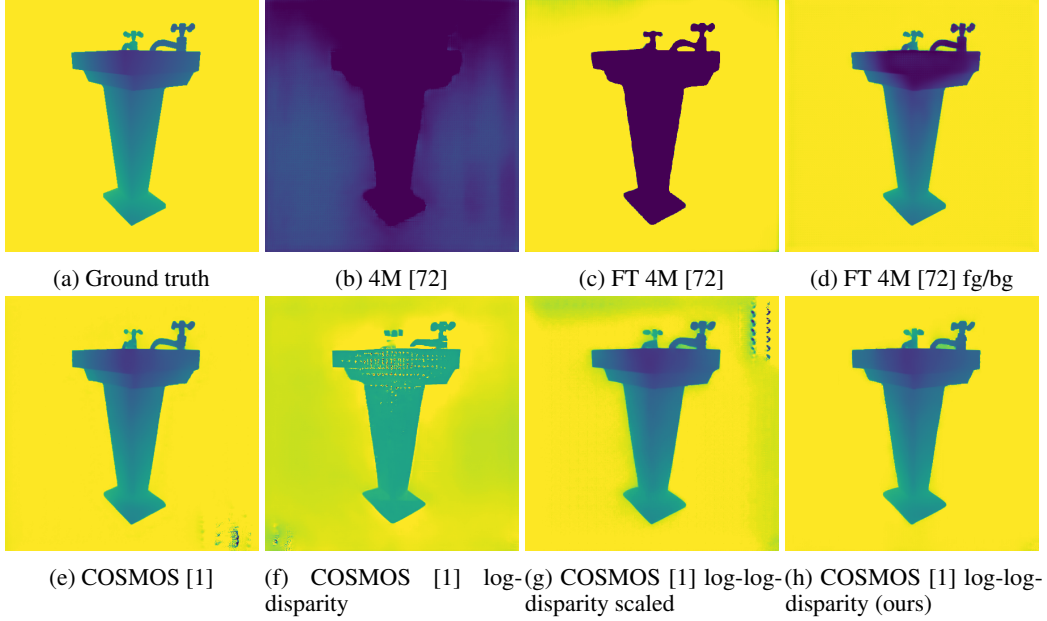


Figure 18: **Depth tokenizer.** Qualitative comparison of different depth tokenization approaches.

ground. Finally, we apply a log-log transform to the disparity, $d_{log} = \log(\log(d + 1))$. This double logarithm aggressively squashes the extreme long-tail disparity distribution, which ranges from 1 to 10^6 given our choice of ϵ , into a dynamic range that is highly compatible with the natural-image priors of the tokenizer. Empirically, these transformations enable high-fidelity depth tokenization using the unmodified COSMOS tokenizer [1] (see Fig. 18h). We also tested scaling the log-log distribution (Fig. 18g) to strictly match the COSMOS RGB dynamic range, but this reintroduced artifacts, confirming that our unscaled log-log disparity is the optimal processing pipeline. Ultimately, this pipeline yields 196 tokens per view for both RGB and depth modalities.

Normals & Masks: We finetune the tokenizers from 4M-21 [7] using their original training objectives to account for the domain gap between the pseudo-labeled modalities obtained with expert models from real-world images and our rendered values. The normal map tokenizer is a diffusion-based VAE [88], and the mask tokenizer is a ViT-based [24] VQ-VAE [98]. For normals, we transform the global normal values obtained from Blender [18] into view-space normal vectors, ensuring that they remain invariant to the object’s global orientation. We normalize the resulting view-specific normals to unit length and linearly map their components from $[-1, 1]$ to $[0, 1]$ to use the standard RGB processing pipeline. For masks, we likewise adopt the standard image processing pipeline and binarize the resulting image to serve as the ground-truth target for the binary cross-entropy loss. Since the masks in 4M-21 [7] were originally designed for SAM instances, they operate at a spatial resolution of 64^2 , which is insufficient to represent fine object details. We address this limitation by increasing the resolution to 224^2 and bilinearly interpolating the positional embeddings of the patches, leveraging the flexibility of the underlying ViT architecture.

Edges & Features: We tokenize the edge and feature modalities using the pretrained tokenizers from 4M-21 [7]. The edge tokenizer is a VQ-VAE with a diffusion decoder [88] that produces 196 tokens per view. The global DINOv2 tokenizer is a bottleneck-MLP discrete VAE with Memcodes quantization [70], yielding 16 tokens per view. Dense DINOv2 and CLIP features are tokenized into 256 and 196 tokens, respectively, using ViT-based VQ-VAEs [98].

B.2 3D as Dense 2D

We tokenize triplane-based modalities with 2D VQ-VAEs, processing the three planes separately. We find that this independent processing improves reconstruction quality by exploiting the orthogonal decomposition of the 3D field, inherently promoting equivariance to spatial axis permutations. In

Table 5: Voxel tokenizer performance with different training loss functions. We find that L2 loss with no sigmoid applied before loss computation has the best performance but overall performance is very similar across losses.

Loss function	Accuracy (%) $\uparrow$	F1 score $\uparrow$
Binary Cross Entropy	99.06	0.872
L2	99.07	0.875
L2 (no sigmoid)	99.12	0.880

practice, we concatenate the three planes along the batch dimension for independent processing. Each modality uses different tokenizer components to improve performance.

NeRF Weights: We tokenize NeRF weight triplanes with a VQ-VAE that uses a ViT-B encoder and decoder with a vocabulary size of 8,192. We encode each plane with a patch size of 2, compressing each plane into 1,024 tokens, for a total of 3,072 tokens per triplane. In addition to the standard L2 reconstruction loss, we apply an LPIPS loss to renders from the predicted triplanes. The LPIPS loss is weighted $2\times$ more strongly than the other losses.

Part Features: We tokenize part feature triplanes with a VQ-VAE that uses a ViT-B encoder with a patch size of 8 and a vocabulary size of 8,192. Each plane is therefore compressed into 256 tokens, for a total of 768 tokens per triplane. We use a Patched Diffusion Model decoder with a patch size of 2 to obtain sharp results.

B.3 3D as Dense 3D

B.3.1 Voxels, UDFs & NeRF Grids:

We tokenize modalities represented as dense 3D grids with 3D VQ-VAEs that use 3D-CNN encoders and decoders, downsampling the modalities by a factor of 8 and using a vocabulary of 8,192.

For voxels, we found that training with L2 reconstruction and thresholding the final output marginally improves performance over binary cross-entropy loss (Tab. 5). Each voxel grid is compressed into 64 tokens.

For UDF and NeRF grids, we likewise use L2 reconstruction, as it produces high-quality reconstructions without other modifications. Each of these grids is compressed into 512 tokens.

B.3.2 Trellis Latents (3DGS)

The Trellis-SLATs are a sparse representation in a 64^3 voxel space, in which only active (surface) voxels carry information. To tokenize these SLATs, we convert the sparse structure into a dense grid, setting inactive voxel representations to zero. We train a 3D-CNN-based VQ-VAE [98] that downsamples the representation to 16^3 voxels with a discrete quantization bottleneck, yielding 4,096 tokens per object. The 3D-CNN decoder has two heads: one predicts an occupancy map, *i.e.*, the active-voxel structure, and the other predicts the latents, which are gated by the active-voxel prediction to produce the final SLATs. In addition to reconstruction losses on the structured latent, we apply rendering losses by decoding the predicted latent into Gaussian splats. Note that we densify the SLATs for convenience so that they can be used within our generic dense 3D tokenization pipeline. Although this process introduces irrelevant values in inactive voxels, the tokenizer’s bottlenecks and latent quantization compress the resulting representation effectively.

As shown in Tab. 6, we found that downsampling to an 8^3 representation (using 512 tokens per object) yields a high loss and leads to inconsistent, poor reconstructions, especially for cases with fine shape or texture details. Furthermore, the separate occupancy prediction and reconstruction losses provide significant performance improvements.

B.4 Other 3D Modalities

Mesh Geometry: To tokenize mesh geometry, we use the pretrained Cube tokenizer. The Cube tokenizer takes 8,192 points and surface normals, which we sample from the surface of the Objaverse-XL meshes. Each mesh is compressed into 512 tokens with a codebook size of 16,384.

Table 6: **Trellis tokenizer ablations.** We find that using an occupancy (occ.) loss significantly improves the results, while increasing the number of tokens per object from 512 (8^3) to 4,096 (16^3) further improves reconstruction quality. The reconstruction loss is binary cross-entropy (BCE), while the rendering loss combines MSE, LPIPS, and SSIM.

Method	Reconstruction Loss ↓	Rendering loss ↓
512 tokens	0.037	0.149
512 tokens + Occ. Loss	0.024	0.051
4096 tokens + Occ. Loss	0.009	0.035

Table 7: ULIP-2 tokenizer performance for various codebook sizes

# Codebooks	Cosine Similarity ↑	BLEU (ModelNet40) ↑	BLEU (Lvis) ↑
8	0.93	0.80	0.71
32	0.95	0.85	0.78
128	0.97	0.89	0.84
256	0.98	0.91	0.87
512	0.98	0.98	0.86
1024	0.97	0.87	0.81

ULIP-2 Embeddings: We train a discrete VAE with Memcodes quantization [70], a codebook of size 256, *i.e.*, 256 distinct tokens, and a bottleneck-MLP [6] encoder and decoder. This codebook size optimizes reconstruction performance while minimizing the number of tokens needed to represent the embedding (Tab. 7). We train the tokenizer for 30 epochs using a cosine-similarity loss.

C Model Architecture

OmniDiMM is a modified Transformer encoder-decoder model [99], with changes designed to improve performance and ease of training. Full model settings are listed in Tab. 8.

C.1 Model Structure

Prior work shows that increasing transformer depth is a more efficient way to achieve performance gains at this scale [94, 43, 4]. Therefore, we make both the transformer encoder and decoder deeper than in standard transformer models by following a *DeepNarrow* strategy [94], using 36 blocks in each. We use a transformer block with $dim = 1024$ and 16 attention heads, keeping the dimension per head fixed at 64, while setting the MLP size to the standard ratio of $4 \times dim$ [23, 82]. Overall, this makes OmniDiMM a 1 billion parameter model. Such deep, narrow models can be unstable during training, so we apply LayerNorm Scaling (LNS) to improve stability [92]. In a small-scale proxy sweep, we empirically find that applying LNS both after LayerNorm [5] and after the attention and MLP layers yields the best results. We use SwiGLU activations [87] and no biases, which has been shown to improve performance [7]. We also use query-key normalization [35] to ensure stable training across modalities with widely varying token counts. Finally, we apply μ -P [120] parameter scalings to enable effective hyperparameter transfer from small-scale proxies.

C.2 Positional & Modality Embeddings

To enable OmniDiMM to distinguish tokens from different modalities, we add learnable modality embeddings to the embedded tokens. The modality embeddings have the same dimensionality as the embedded tokens and are shared within each modality. Positional embeddings are applied according to the modality type (Fig. 5).

Text Positional Embeddings: We add fixed 1D sine-cosine embeddings to caption token embeddings.

Multi-view 2D Positional Embeddings: We extract Plücker rays [77] from the ground-truth camera poses of the renders to describe the source camera location of each view for 2D modalities. Each ray is a 6D vector that describes the direction and moment of the frustum cast from the camera that

generated the image patch centered at a given token. Thus, the Plücker rays connect image patches to the corresponding 3D locations from which they were generated, bridging 2D and 3D. We further augment these rays with 2D screen Normalized Device Coordinates (NDCs) to provide image-space location information, similar to RayDiffusion [125]. The resulting 8D position vector is encoded with a small feedforward encoder comprising two linear layers separated by a GeLU activation [34], with a hidden dimension of 128.

Global multi-view features instead use only the directional component of the Plücker rays to distinguish different views, because the moments average to zero and the tokens are not patch-aligned, but instead represent feature components that are not aligned with 3D space. We therefore add an additional 1D sine-cosine embedding for tokens within a single view.

3D Positional Embeddings: For 3D modalities represented as dense 3D grids, we use 3D sine-cosine positional embeddings to encode token positions. For modalities represented as triplanes, the position within each plane is encoded with 2D sine-cosine positional embeddings. The three planes are distinguished by adding a plane token that is unique to the XY , XZ , and YZ planes.

ULIP-2 Positional Embeddings: Because ULIP-2 embeddings [119] are global features, we use learnable positional embeddings to encode positional information, following the same reasoning as in 4M-21 [7].

D Data Sampling

Similar to 4M [72], the distribution of tokens observed during masked modeling is controlled by Dirichlet distributions with parameters α_m for each modality m . Varying α_m controls the sharpness of the distribution and the probability that tokens are sampled from a given modality. If all $\alpha_m < 1$, the sampling is sharper, and entire modalities are more frequently preserved within a sample. Conversely, if all $\alpha_m > 1$, the sampling is smoother, and multiple modalities contribute to each sample more often. A higher α_m value relative to those of other modalities increases the likelihood that the corresponding modality will be sampled; that is, if $\alpha_{m_1} < \alpha_{m_2}$, then m_2 will be sampled more frequently than m_1 . When multiple α mixes are used, their frequencies determine the probability that a given mix is selected for a sample.

D.1 Pretraining α Mixes

In contrast to 4M-21 [7], we implement multiple task-specific sampling mixes to ensure that the model encounters important tasks frequently during pretraining. This is necessary because the number of tokens per modality varies substantially, meaning that some important tasks, such as NVS or single-view 3D generation, would otherwise appear very infrequently during training under a fully random sampling approach. The α mixes we use are:

- **Any-to-any:** The four masking strategies introduced in 4M-21 [7], with both input and output α_m symmetrically set to 0.01, 0.1, 1.0, and 10.0, respectively, for all m . Each mix is seen with frequency 10.
- **RGB-to-RGB:** Predict RGB image tokens from either raw RGB patches or other RGB image tokens, thereby training NVS from RGB. These two mixes are each seen with frequency 5.
- **RGB-to-others:** Predict other modalities from either raw or tokenized RGB, both with input $\alpha = 0.01$ to induce a ‘sharp’ sampling distribution. There are three different target mixes: 2D outputs only (multimodal NVS from RGB, frequency 5), 3D outputs only (3D generation, frequency 5), or all modalities as outputs (frequency 10). The target α_m values are set to 0.5 for all 2D modalities, all 3D modalities, and all modalities, respectively.
- **2D-to-others:** Two mixes predict from 2D inputs only. All 2D modalities have input α set to 0.5, and the target α values are set to 0.5 for all 2D modalities (complete multimodal NVS, frequency 10) and all 3D modalities (multimodal 3D generation, frequency 5).
- **3D-to-others:** Three mixes predict from 3D inputs only. All 3D modalities have input α set to 0.5, and the target α values are set to 0.5 for all 3D modalities (multimodal 3D modeling, frequency 5), all 2D modalities (multimodal rendering, frequency 10), and RGB only (rendering, frequency 5).

- **Text generation:** Text tokens are used as the only input, and all other modalities have target α set to either 0.05 or 0.5, corresponding to ‘sharp’ and ‘smooth’ target distributions. Both mixes have frequency 2.5.

E Training Method

E.1 Pretraining

Objective: We train OmniDiMM with a multimodal masked modeling objective. This involves conditioning the Transformer [99] encoder on a small subset of input tokens from all modalities and predicting a different, non-overlapping subset of target tokens with the Transformer decoder. This objective teaches the model to predict any random portion of a multimodal sample from any arbitrary conditioning tokens, which has been shown to enable full modality generation at inference time. We optimize OmniDiMM by minimizing the cross-entropy loss over the target tokens in each sample. This loss is applied irrespective of the underlying modality, eliminating the need for modality-specific loss balancing.

Each sample consists of at most 17,160 tokens, as we randomly sample between 1 and 5 views for each multi-view 2D modality from the 20 views available in our dataset. We sample 512 tokens as encoder inputs and 512 tokens as targets for each sample, so the model sees only 3% of the full sample. The tokens chosen as inputs and targets are determined by the α -mix settings described in Sec. D. We apply uniform random masking to 2D and 3D modalities and span masking to text.

Multi-Dataset Use: 3DGSs are expensive to pseudolabel, as each sample requires 100 renders with specific rendering settings. We therefore train on two datasets: one that includes raw RGB, which is slow to train on, and one that includes 3DGSs. The dataset including 3DGSs contains 500k objects, while the raw-RGB-inclusive dataset contains all 972k objects. During training, we sample from each dataset with probability 0.5.

Optimizer: We use an AdamW [63] optimizer with a Warmup-Stable-Decay (WSD) learning rate scheduler [41] and square-root decay [26] to enable resumable pretraining. We observe similar performance for models trained with WSD scheduling and with cosine scheduling. Recent work has found that weight decay should be scaled relative to model and dataset size [104]. Accordingly, we schedule weight decay according to power laws [9] relative to the number of tokens seen at any point during training.

Hyperparameter Optimization: Because we implement μ -P transfer in OmniDiMM, we can readily transfer hyperparameters from a small-scale proxy to the full model. We therefore sweep over the optimizer, parameter initialization, and μ -P alpha and power-law parameters using a transformer with $dim = 128$, which is $8\times$ narrower than OmniDiMM. We run 50 trials of 20 billion tokens each using the Tree-structured Parzen Estimator [107] in Optuna [3]. The optimal hyperparameters are listed in Tab. 8.

Training schedule: We train OmniDiMM with the optimized hyperparameters for a total of 900B tokens, including 1B tokens of linear warm-up and 100B tokens of square-root cooldown.

F Transfer Experiments

To demonstrate the versatility of OmniDiMM as a foundational backbone, we evaluate its representation learning capabilities across diverse downstream tasks by appending task-specific heads to the encoder. Although task-specific modality chaining often yields superior results, as evidenced by our NVS improvements in Sec. 5.1, we intentionally employ a standardized fine-tuning recipe. This approach isolates the inherent quality of the pretrained features and demonstrates the model’s efficacy as a robust, off-the-shelf feature extractor. Specifically, we freeze the core encoder weights and inject LoRA [40] modules into the attention layers, setting both the rank and α to 32. We optimize the full model, *i.e.*, the encoder and task-specific heads, using AdamW [63] with a base learning rate of 10^{-4} and a weight decay of 0.05, consistent with our pretraining configuration. Finally, to preserve the robust multimodal priors captured in the earlier layers while enabling stronger adaptation in the deeper network stages and the randomly initialized heads, we apply a layer-wise learning rate decay [17] of 0.85, mirroring the transfer learning protocol established by 4M-21 [7].

Table 8: Pre-training configuration used for OmniDiMM

Hyperparameter	OmniDiMM
# Encoder Blocks	36
# Decoder Blocks	36
dim	1024
# Attn heads	16
Feedforward activation	SwiGLU [87]
Use bias?	False
Post LayerNorm LNS	True
Post attn/MLP LNS	True
QK-norm	True
Input token budget	512
Target token budget	512
Max tokens per sample	17,160
Data sampling	Random & per task (Sec. A.1)
Image size	224^2
# 2D views	$n \in \{1, 2, 3, 4, 5\}$
Repeated sampling	10
Data type	bfloat16
Optimizer	AdamW [63]
Opt. Momentum	$\beta_1 = 0.88, \beta_2 = 0.948$
Opt. Epsilon	$\epsilon = 4.2 \times 10^{-8}$
Learning Rate (LR) Schedule	WSD [41]
LR cooldown shape	Square root decay [26]
Max LR	0.002
Weight Decay (WD) schedule	Power lines (Sec. E)
Max WD	0.37
WD c_τ	1.126
WD m_τ	-0.509
μ -P weight init σ	0.0135
μ -P α_{in}	1.485
μ -P α_{out}	1.776
Training length (# tokens)	900B
Warmup length (# tokens)	1B
Cooldown length (# tokens)	100B
Batch size	4080

F.1 Object Classification

To demonstrate OmniDiMM’s ability to fuse different input modalities for a downstream task, we evaluate it on the ModelNet40 [111] classification benchmark. Inspired by the zero-shot results of ULIP-2 [119], we test the effect of augmenting ULIP-2 features with additional input modalities. The intuition is that redundancy across modalities reduces modality-specific noise, while their complementary information improves overall perception.

Because the sequence length of the encoder output varies with the number of input modalities, we aggregate these features using a cross-attention layer. Specifically, we define the attention queries as learned embeddings representing each target class (*i.e.*, the 40 classes of ModelNet40 [111]), while the encoder outputs serve as the keys and values. Before this aggregation, we project the encoder outputs through an MLP and add the modality-specific positional embeddings element-wise, mirroring the architecture of the OmniDiMM decoder. Finally, we apply layer normalization [5] to the aggregated class features and linearly project each feature to a single logit per class.

We train the classification head and adapt the backbone end-to-end using a standard cross-entropy loss for 50 epochs. To obtain the tokenized input modalities, we employ the same modality generation



Figure 19: **Additional qualitative NOCS transfer examples.** Predicted masks and NOCS overlaid on the original image. The two left images are from ARKITScenes [8] while the two right images are from NOCS-Real275 [100].

pipeline used for the pretraining data (see Sec. A). For all experiments, we use ULIP-2 embeddings as a foundational input. In the *3D-only* configuration, we additionally incorporate Signed Distance Functions (SDFs) and voxel grids. In the *2D/3D semantic* configuration, we instead include dense DINOv2 [75] and CLIP [81] feature maps extracted from five random views sampled independently for each object and modality. Refer to Tab. 4 for the quantitative results.

F.2 2D Object Pose Estimation

While object classification is closely aligned with our pretraining data, OmniDiMM also adapts seamlessly to tasks involving single-view inputs and real-world images. To showcase this capability, we evaluate our model on 2D object pose estimation, which we frame as a NOCS prediction problem [100]. Concretely, we replace the DINOv2 [75] backbone used in OmniNOCS [53] with OmniDiMM and retain the same DPT head [47] to fuse intermediate layer features and predict both a NOCS map and a validity mask. We further predict object sizes, 3D centroids, and the rotations of the enclosing 3D bounding boxes with convolutional heads. The input to OmniDiMM consists of a single image provided through the raw RGB modality; following the OmniNOCS protocol [53], we obtain it by applying RoIAlign [33] to the original image using the provided 2D bounding boxes. We train the full model end to end with the same loss as OmniNOCS [53], using our default transfer hyperparameters.

In Sec. 6, we compare OmniDiMM against the original NOCS baseline [100] and OmniNOCS [53] on the NOCS-Real275 evaluation set. The original NOCS baseline [100] is trained directly on the NOCS-Real275 training split. In contrast, OmniNOCS [53] is trained on a large aggregated mixture containing around half a million instances, including proprietary subsets such as the NOCS annotations for the Waymo dataset [91]. For evaluation on NOCS-Real275, the OmniNOCS authors explicitly excluded this dataset from their training mixture, making their result a measure of zero-shot cross-dataset transfer.

Our fine-tuning setup for OmniDiMM operates under different constraints. We use a substantially smaller, strictly open-source subset of the OmniNOCS data aggregation [53]. Specifically, our training mixture comprises NOCS-Real275 [100], Objectron [2], KITTI [31], and ARKITScenes [8], *i.e.*, 4 of the 11 datasets included in the OmniNOCS mixture. Together, these datasets account for roughly 27% of the total images and 19% of the total instances. Because our overall data volume is much smaller than that used by OmniNOCS, and because neither the OmniNOCS code nor model is public, we include the NOCS-Real275 training split in our fine-tuning mixture to provide sufficient in-domain supervision. Consequently, although OmniDiMM is trained on far less data overall than OmniNOCS, it shares the advantage of in-domain training data with the original NOCS baseline. The test split of NOCS-Real275 remains strictly unseen during training.

In Fig. 10 we can see how OmniDiMM is able to predict accurate NOCS and instance masks. Left image is from NOCS-Real275 [100] and the right one from Objectron [2]. We provide some additional visualizations in Fig. 19.

F.3 Grasp Prediction

Finally, we evaluate OmniDiMM on the challenging task of dexterous grasping. The goal is to predict the full set of articulation parameters across all degrees of freedom of a robotic hand (specifically, a ShadowHand) so that it can execute a stable, physically plausible grasp. Given the complexity of hand-object interactions, this problem demands highly accurate 3D geometric perception. Whereas

Table 9: **Grasp prediction transfer.** Metrics on the MultiDex [58] dataset, including grasp success rates (Suc.6 and Suc.1), maximum penetration, and the diversity of the predicted grasps. A grasp is considered successful if the object’s displacement under perturbation is at most 2 cm in at least one direction (Suc.1) or in all six axis-aligned directions (Suc.6). We compute these metrics by simulating the predicted grasps in IsaacGym [69].

Method	Suc.6 $\uparrow$	Suc.1 $\uparrow$	Pen. $\downarrow$	Div $\uparrow$
UniDexGrasp [117]	23.7	65.5	24.5	0.14
GraspTTA [50]	21.0	65.3	21.2	0.10
SceneDiffuser [46]	28.3	74.8	25.1	0.15
UGG [66]	46.0	83.2	24.5	0.14
DGA [130]	54.8	90.8	18.9	0.25
DGA w/ LLM [130]	53.1	91.2	18.8	0.23
OmnDiMM (ours) w/ standard diffusion sampling	3.6	83.9	13.2	0.11
OmnDiMM (ours) w/ physics-guided sampling [130]	83.3	96.7	15.9	0.16

most existing approaches rely on sparse point clouds as input [130, 117, 50, 46, 66], multi-view images provide a richer and denser signal, offering stronger cues for detailed surface geometry estimation. Although OmnDiMM natively supports a broad range of input modalities for downstream tasks, as demonstrated in Sec. F.1, we restrict the input in this experiment to raw multi-view RGB. This design choice highlights the model’s practical utility by showing that it can extract robust 3D spatial understanding directly from readily available real-world camera inputs.

We follow the architecture of DexGrasp Anything [130], replacing its Point Transformer [129] backbone with OmnDiMM while retaining the original training objective. We use the text-unconditioned variant of DexGrasp Anything to ensure that grasp generation is driven solely by the visual features extracted by OmnDiMM. These features then condition a U-Net [85], which iteratively denoises the hand articulation parameters.

We present a quantitative comparison between OmnDiMM and task-specific baselines on the MultiDex dataset [58] in Tab. 9. We first evaluate our method using standard DDPM sampling [36] at inference time. Under this regime, the model achieves a near-zero success rate when subjected to external forces along all axis-aligned directions. However, it maintains a high success rate under single-direction perturbations. Together with the low penetration values, this suggests that vanilla sampling tends to produce brittle, superficial contacts rather than robust, force-resistant grasps. In contrast, when combined with the physics-guided sampler introduced by DexGrasp Anything [130], OmnDiMM outperforms all task-specific baselines on the success metrics. The only metric on which our method trails is grasp diversity, suggesting that the predicted distributions capture highly accurate but more sharply concentrated modes of valid grasps than prior methods.

When interpreting these results, it is important to account for the differences in input modality across the evaluated methods. Whereas the baseline models take sparse point clouds as their sole input, OmnDiMM is conditioned primarily on dense multi-view RGB observations. In addition, the physics-guided sampler iteratively refines the predicted hand parameter distribution using collision and contact heuristics derived from an input point cloud. As a result, our full pipeline operates in a richer multimodal setting, combining the dense geometric cues of multi-view images for global feature extraction with the explicit spatial constraints provided by point clouds during sampling. We provide additional qualitative grasp predictions in Fig. 20.

G Computational Resources

Training the final 1B version of OmnDiMM was done on 64 4xH200 120GB nodes for 7 days. Models used in ablations that are trained for 500B tokens can be trained in 3.5 days on the same compute.

The tokenizers each took varying amounts of time to train. The UDF, Voxel, NeRF grid and ULIP-2 tokenizers each took 24 hours to train on 8 A100 GPUs, while the partfield and NeRF weight tokenizers required training on 6 4xH200 GPU nodes for 2 days. The 3DGS tokenizer took 12 hours to train on 32 4xH200 GPU nodes.

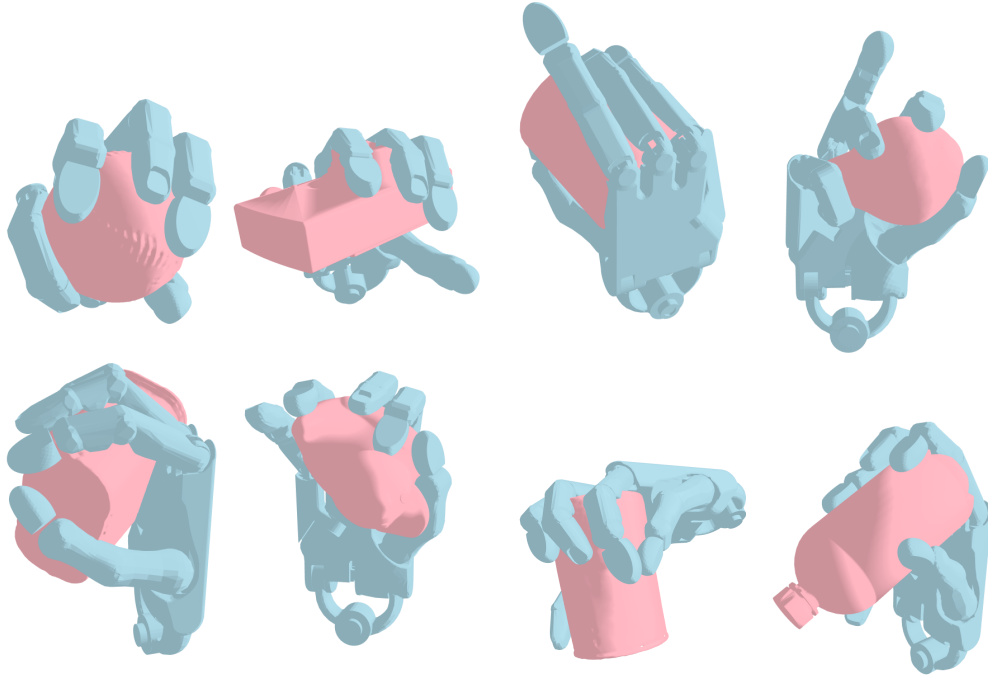


Figure 20: **Additional sample grasps.** Predictions by OmniDiMM on objects from MultiDex [58].

This research project used beyond the compute stated here through an extensive development period of both the 3D tokenizers and the OmniDiMM model.

H Broader Impact

OmniDiMM is an any-to-any foundation model capable of natively operating across dimensions. We have intentionally developed a general framework that can be re-employed by other practitioners who wish to learn from cross-dimensional data. Previous large-scale multimodal models have been adapted for scientific discovery [127, 73, 110, 76], and it is our hope that our generalization of the data forms that can be accepted by any-to-any multimodal models will further this effort. We are committed to open-sourcing our models, code, and data to enable broad interaction with our model and framework.

As our model is capable of any-to-any prediction, it is inherently a generative model, and as such, has the capacity to be used to develop content that may have negative societal impacts. While our model is currently not likely to be capable of such harm due to the limitations brought on by its smaller relative data and model scale, our proposed framework allows for generation from arbitrary input forms, which may pose risks when scaled. Our model was trained on an open source dataset, Objaverse-XL [20], and as such, the data that it has observed is public. We hope that this, along with our commitment to open-sourcing our work, will provide transparency as to our model’s capabilities and enable quick action if issues arise with the data used that are currently unknown to the community.